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RESEARCHPAPER

AI-Based Tuberculosis Detection Using Chest Radiographs and Transfer Learning

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***Abstract*—Early and accurate diagnosis of tuberculosis (TB) is essential to stop its transmission, especially in underdeveloped countries. A limitation of traditional diagnostic tests is that they typically require hours of assessment; they are also prone to human error in interpretation and cannot be scaled up in limited resource settings. This research proposes a machine learning-based (ML) system for automatic and efficient diagnosis of TB in CXRs, addressing these limitations. The proposed technique enhances the image quality when applied to the TBX11K database and the pre-processing consists of conversion to greyscale, picture scaling, Contrast Limited Adaptive Histogram Equalization (CLAHE) and normalization. Supplementing data with synthetic minority In order to rectify class imbalance and enhance dataset variety, SMOTE is utilized. After processing, images were categorized by Extreme Gradient Boosting (XGBoost) method. The data is divided into three sets: training, validation, and testing sets, so as to develop a complete model and test the effectiveness of the model. The suggested framework is proven effective in the experiments, which achieved an F1-score of 99.60%, an ACC of 99.71%, a PRE of 99.70%, and a REC of 99.74%. Analyses comparing the suggested method to preexisting ML and DL models have proven its higher classification performance. Automatic TB screening and early detection utilizing chest radiographs is now possible with the help of the created framework, according to the results. It's dependable, efficient, and accurate.**

Keywords—Tuberculosis Detection, Deep Learning, Chest X-ray (CXR) Analysis, Artificial Intelligence in Healthcare, Contrast Limited Adaptive Histogram Equalization (CLAHE), Healthcare.

I. INTRODUCTION

Healthcare systems worldwide continuously strive to prevent infectious diseases through early diagnosis, effective treatment, and improved public health strategies. Annually, tuberculosis (TB) causes millions of illnesses and deaths, making it one of the most frequent infectious diseases globally [1][2]. This has to be addressed since it is a big problem in public health. Lungs are the most common sites of TB infection, however the disease can extend to other tissues as well [3]. Droplets expelled into the air by infected people's coughs or sneezes are the primary vector for the transmission of tuberculosis. Controlling disease spread and minimizing mortality need early diagnosis and appropriate treatment. Tuberculosis (TB) is a significant issue despite the ongoing improvement of health care and medical research. This is especially true in developing and emerging nations [4][5][6].

A chest X-ray, often known as chest radiography, is a standard diagnostic tool for a variety of lung diseases, including tuberculosis [7][8]. Radiographs of the chest are important in mass screening programs as they: are affordable; widely available; and easily accessible [9]. Symptoms and signs of TB are very variable from person to person and may be mistaken for other lung diseases such as pneumonia, fibrosis or sarcoidosis, making chest X-ray images difficult to interpret [10][11]. Also, minor irregularities could be missed and the diagnosis and treatment could be delayed.

The advent of digital medical imaging gave birth to a number of computer-aided diagnostic tools that seek to automate the process of illness diagnosis [12][13]. Recently, the use of artificial intelligence (AI) techniques to analyze chest radiographs and to recognize patterns which are beyond human capabilities have shown a great potential for this approach [14]. In regions where there are fewer trained radiologists, AI-powered solutions can help reduce inter-observer variability and enhance diagnostic consistency [15]. These are very useful features that can be used to enhance the process of tuberculosis screening and detection using AI diagnostic systems [16].

The use of AI technologies, such as DL and ML, has revolutionized the analysis of medical images. There are ample reports of DL or ML techniques improving medical image analysis and automated disease diagnosis [17]. These methods can reliably separate TB-positive people from normal people using chest X-ray image data, which can be used to learn complex patterns. Minimizing human involvement and improving diagnostic uniformity can support the early detection and treatment of TB and facilitate clinical decision-making through the use of ML/DL systems [18].

A. Motivation and Contribution

This study is motivated by the increasing worldwide TB burden and the need for an accurate, fast and automated TB diagnostic platform for early diagnosis. Access to specialized radiologists is limited in many developing countries, potentially leading to delayed diagnosis of chest radiograph and misdiagnosis. A robust machine learning tool is therefore needed to assist with TB screening. This is a grassroots initiative to improve the validity of the diagnosis, and to assist healthcare systems in low resource environments. This research offers several key contributions as listed below:

- Classified and detected Tuberculosis on the TBX11K chest X-ray dataset.
- Build a system to diagnose tuberculosis (TB) automatically by analyzing chest X-rays and applying the XGBoost algorithm for ML.
- Utilized data augmentation strategies to enhance the model's capacity to generalize and boost dataset diversity.

- Utilized the SMOTE to rectify class imbalance, guaranteeing that training represented all classes equally.
- Conducted a comparative analysis with ResNet50, VGG16, and MobileNet-V2, demonstrating the effectiveness of the proposed XGBoost-based approach.
- Used industry-standard performance measures to assess the suggested model, including ACC, PRE, REC, F1, and ROC analysis.
- Provided a reliable and computationally efficient solution for early tuberculosis diagnosis and large-scale screening using chest X-ray images.

B. *Justification and Novelty*

TB is hard to diagnose, and patients need to get the right medicine at the right time to stop the disease from spreading and improve their health. Automated chest X-ray analysis is an affordable and scalable approach, especially in resource-poor areas where expert radiologists may not be available. This research adds to the existing literature by creating a unique TB detection framework based on XGBoost. The system enhances classification accuracy with the help of picture preprocessing, augmentation, and SMOTE-based class balancing. The proposed approach achieved outstanding classification ACC on the TBX11K database and showed promising results across all evaluation metrics, making it a useful tool for automated TB screening and diagnosis.

C. *Organization of the Paper*

The paper is organized as follows: Section II provides a literature review on recent studies. Section III proposed a method for the TB Detection System. Section IV discuss with Performance evaluation for the TB detection system. Section V conclusion and the future research.

II. LITERATURE REVIEW

A comprehensive review and analysis of key research studies on Tuberculosis Detection Using Chest Radiographs was conducted to inform this study. Table I presents an overview of recent works, including models, datasets, findings, and challenges, highlighting key research gaps.

Navalan, Vinoth, Balakrishnan, et al. (2026) propose TB-GuardNet, an energy-efficient hybrid Transformer–CNN framework for automated tuberculosis (TB) screening using chest radiographs (CXR). The model combines the contextual learning capabilities of Transformers with the spatial feature-extraction strength of CNNs and employs adaptive feature fusion to balance local and global representations. Experimental evaluation on the MC, Shenzhen, and NIH ChestX-ray14 datasets demonstrates superior performance, achieving 98.6% ACC, 98.1% sensitivity, and a 27% reduction in inference energy consumption compared with transformer-only models [19].

Akilandeswari (2025) offer a combined approach to classifying chest X-ray pictures using Discrete Wavelet Transform and features derived from Convolutional Neural Networks based on LeNet. DWT breaks down pictures into their respective frequency bands, whereas LeNet does feature extraction. Boost, Random Forest, and Support Vector Machine classifiers are tested with these combined characteristics. Grey Wolf Optimizer can further optimize feature selection, resulting in even better outcomes. A 97.1% success rate was achieved by the fine-tuned Random Forest classifier [20].

Rajak et al. (2025) developed DL methods for tuberculosis diagnosis with chest X-ray pictures. At first, an analogue CNN model got an ACC of 82.69%. To enhance performance, transfer learning with the VGG16 model was employed, increasing the detection ACC to 90.38%. The proposed approach improved feature extraction, reduced training time, and enabled the identification of complex radiographic patterns. The findings demonstrate its potential to assist radiologists in the early diagnosis and effective management of TB in clinical practice [21].

Ramadasan et al. (2024) The goal is to create a tool that can diagnose pneumonia (viral and bacterial) with the use of DL. This tool's steps are as follows: data collecting, resizing, contrast enhancement, feature extraction using a pre-trained DL algorithm, deep-features reduction with 50% dropout, serial features integration, binary classification and verification. I using individual deep-features, (ii) reduced-features, and (iii) fused deep-features in the experimental study on the selected database. The experiment involved using RF aided classification, which, when taking the fused deep-features into account, yielded an ACC of over 98% [22].

Hossain, Alam Nipu and Hasan (2023) built a CNN model from the ground up to identify TB in chest X-ray pictures, and evaluated its efficacy against that of a multi-layer CNN model and transfer learning using Mobile Net. Publicly available Kaggle datasets were utilized along with image preprocessing, data augmentation, and RMSprop optimization. Experimental results demonstrated that all models achieved satisfactory performance for binary classification, with the proposed CNN architecture attaining the highest ACC of 96.63%, while the multi-layer CNN model achieved 90.00% ACC [23].

Urooj et al. (2022) suggested a system for tuberculosis (TB) identification utilizing chest X-ray (CXR) pictures that is based on stochastic learning and uses ANN. The model incorporates randomness in network initialization and training to optimize feature learning and improve robustness in detecting TB abnormalities with varying geometric characteristics. Experimental evaluation on the Shenzhen and Montgomery datasets demonstrated superior performance, achieving 96.12% sensitivity, 98.01% specificity, 98.45% ACC, and a 95.88% F1, outperforming several state-of-the-art methods [9].

TABLE I. RECENT STUDIES ON TUBERCULOSIS DETECTION USING CHEST RADIOGRAPHS USING MACHINE LEARNING TECHNIQUES

Author	Proposed Work	Dataset	Findings	Limitations & Future Work
Navalan, Vinoth, Balakrishnan et al. (2026)	TB-GuardNet, a hybrid Transformer–CNN framework with adaptive feature fusion	MC, Shenzhen, NIH ChestX-ray14	Achieved 98.6% accuracy and reduced inference energy by 27%	Requires validation on larger multi-center datasets and real-time clinical deployment.
Akilandeswari (2025)	DWT and LeNet-CNN hybrid with optimized feature selection	Chest X-ray dataset	Random Forest achieved 97.1% accuracy	Computational complexity remains high; explainability and generalization need improvement.

Rajak et al., (2025)	CNN and VGG16 transfer learning for TB detection	Chest X-ray dataset	VGG16 improved accuracy from 82.69% to 90.38%	Limited dataset diversity; future work should explore lightweight and robust architectures.
Ramadasan et al., (2024)	Pre-trained deep learning with feature fusion and RF classification for pneumonia detection	Pneumonia chest X-ray database	Achieved >98% accuracy using fused deep features	Focused on pneumonia only; extension to TB and multi-disease classification is needed.
Hossain, Alam Nipu and Hasan (2023)	CNN from scratch and MobileNet transfer learning	Kaggle Chest X-ray dataset	Proposed CNN achieved 96.63% accuracy	Limited generalization across datasets; future work should consider larger and diverse datasets.
Urooj et al., (2022)	Stochastic ANN framework for TB detection	Shenzhen and Montgomery	Achieved 98.45% accuracy and 95.88% F1-score	Model interpretability and scalability to heterogeneous datasets remain challenging.

Research gaps: Existing research on tuberculosis detection from chest radiographs shows that, although DL and hybrid models achieve high performance, several gaps remain. The majority of approaches have high computational demands, which are not suitable for real-time and resource-limited healthcare applications. Many methods are based on small and/or homogeneous data sets, limiting their ability to generalize to other populations and/or clinical situations. Furthermore, several studies have relied heavily on deep architectures without addressing class imbalance and feature optimization. Therefore, there is a need for more efficient, lightweight, and robust models that can provide accurate TB detection with improved generalization and lower computational cost.

III. RESEARCH METHODOLOGY

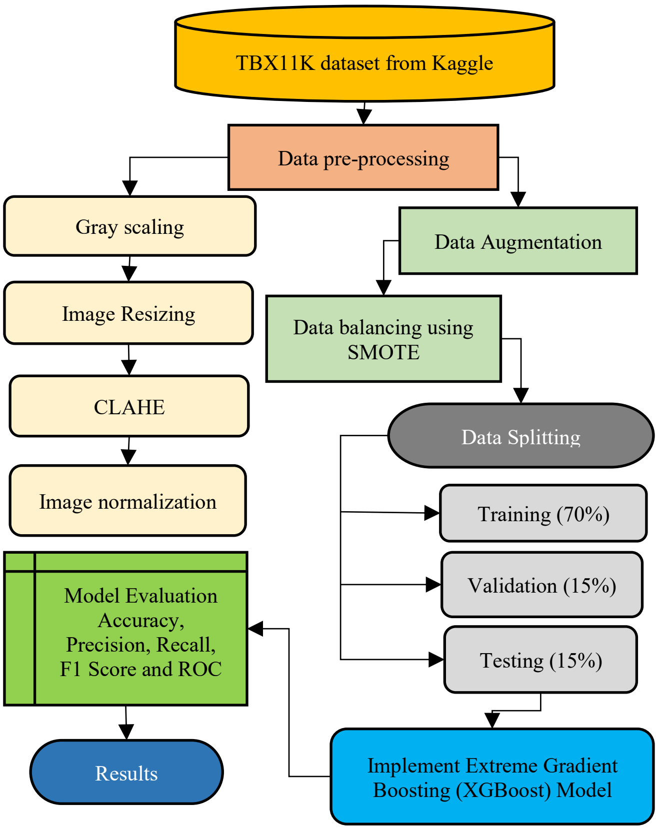

Fig. 1. Proposed flowchart for Tuberculosis Detection Using Chest Radiographs using machine learning

The proposed methodology is based on the TBX11K chest X-ray dataset for tuberculosis detection and uses grayscale conversion, resizing, CLAHE enhancement and image normalization. During the preprocessing phase, data augmentation and balancing procedures based on SMOTE are employed to improve the data sets' diversity and accuracy. Data augmentation and SMOTE-based balancing provide variation and minimize class imbalance before the dataset is separated into training, validation, and testing sets. ACC, PRE, REC, F1, and ROC analysis are some of the performance measures used to train and assess an XGBoost classifier. In Fig. 1 can see the suggested ML pipeline for tuberculosis detection using chest radiographs. Below, finds detailed descriptions of each stage of the proposed approach, outlining the methods and strategies employed throughout the study.

A. Data Gathering and Analysis

Three categories—TB, Healthy, and Sick but Not TB—make up this dataset, which goes by the name TBX11K. The three classes are unbalanced, yet the collection has 11,200 X-ray scans overall. The distribution of the data and the associations between features were examined using bar graphs and other visual representations:

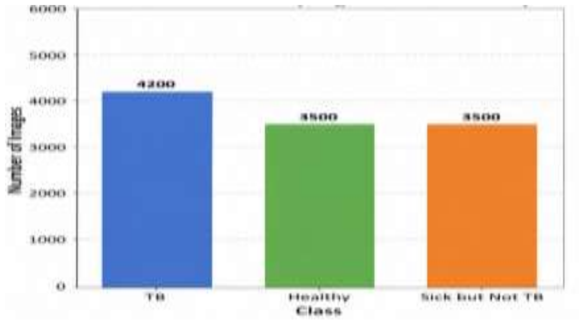

Fig. 2. Bar graph of class distribution

Fig. 2 presents the dataset contains an unequal distribution of chest X-ray images among the classes. The classes are unbalanced because there are more samples in the TB class than in the Healthy and Sick-but-Not-TB classes. This kind of distributional disparity has the potential to cause minority class classification performance issues and biased learning.

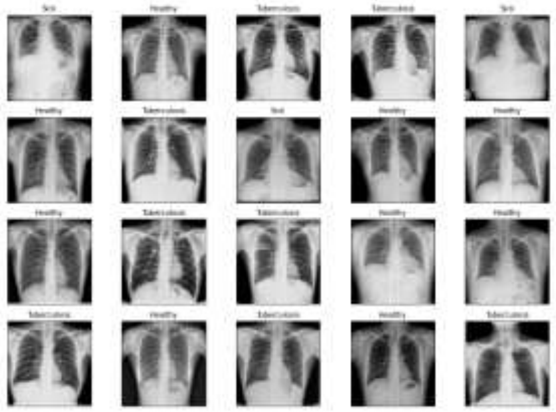

Fig. 3. Dataset Sample Images

The sample chest x-rays for the Healthy, Tuberculosis, and Sick categories are shown in Fig 3. The images differ with respect to their lung appearance and pathological patterns, with some visual differences that are clearly illustrated by the diversity in the lung dataset. The suggested classification model for precise illness detection is trained and tested using these samples [24].

B. Data Pre-processing

The preprocessing of pictures is a prerequisite to their use in model training and inference. This has the potential to speed up both the training of models and the inference process. The following picture preparation methods were employed in this investigation:

- **Gray scaling:** Greyscale picture conversion from RGB is what this is referring about.
- **Image resizing:** The 128 × 128 pixel greyscale picture was resized to a certain size.
- **Contrast Limited Adaptive Histogram Equalization (CLAHE):** The contrast is enhanced, allowing the TB region to stand out more clearly.
- **Image normalization:** One common use of normalization is to create what looks like a more equal distribution of pixel values in an image by adjusting the intensity range of individual pixels.

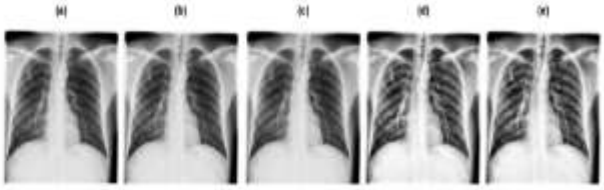

Fig. 4. Preprocessing techniques applied to dataset (a) original image; (b) grayscaling; (c) image resizing; (d) CLAHE; (e) image normalization

Fig 4 shows the methods used to prepare the chest X-ray images for processing. This image is first scaled down to a standard size, then gray scaled, and then CLAHE used to bring out more contrast and specific lung characteristics. Finally, image normalization is applied to standardize pixel intensities for proper model training and analysis.

C. Data Augmentation

The goal of data augmentation is to increase the size of a dataset by drawing more information from already-existing sources. Data that has been somewhat altered from its initial shape by geometric transformations including rotation, vertical and horizontal flipping, and brightness and contrast adjustments is used to diversify the training set.

Fig. 5. Various image augmentation methods employed on dataset: (a) original image; (b) 45-degree rotation; (c) vertical flip; (d) horizontal flip; (e) brightness and contrast adjustments

Figure 5 displays the image augmentation methods employed to diversify the training dataset. To get new looks from the same image, may flip the chest image 45 degrees. Next, turn it upside down once and turn it sideways again. Last but not least, adjust brightness and contrast. These enhancement techniques boost model resilience, minimize overfitting, and increase the generalization ability.

D. Data balancing using SMOTE

Data balancing is intended to make sure that each type of data is represented by an equal number of samples. Overall, it results in increased classification accuracy and a decrease in model bias towards majority classes. A remedy for the dataset's class imbalance was implemented using the SMOTE approach. In this study 1600 images were used of which 800 were healthy and 800 were TB patients and the number of samples taken from both healthy and TB came out to be the same. This balanced distribution can contribute to better model training, prevent bias in the classification process, and provide more reliable prediction results.

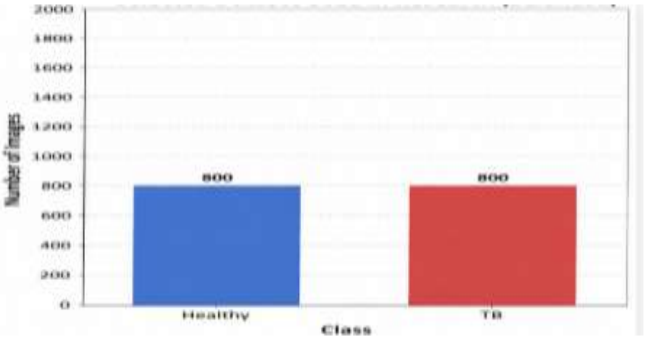

Fig. 6. Class Distribution of the Balanced Dataset Using SMOTE

The Fig 6 illustrates the balanced distribution of Healthy and TB classes obtained after applying the SMOTE. The number of images in both classes is the same (800 images) and it makes the model training less biased with regard to classification.

E. Data Splitting

Training used 70% of the dataset, while validation and testing each received 15%. Model training, hyperparameter adjustment, and fair performance evaluation are all guaranteed by this data splitting approach.

F. Proposed Extreme Gradient Boosting (XGBoost) Model

The XGBoost model is a supervised ML boosting approach that has the potential to enhance the precision of tuberculosis (TB) classification using chest X-ray images. As a means to enable ensemble learning, XGBoost makes use of DTs. Discovering the loss function's value—the disparity between the anticipated and target values—is the first step in fixing a regression problem. One such mathematical expression for the XGBoost regression model is (1):

$$y = f(x) \tag{1}$$

Here, $f(x)$ is the XGBoost model that takes a vector of input attributes (such as square footage and number of bedrooms) and utilizes them to forecast x, where y is the projected property price. In order to calculate $f(x)$, XGBoost first trains a set of decision trees to minimise the MSE loss function. For the final forecast, the model averages the results from all the decision trees. The XGBoost regression model's general form is (2).

$$y = \sum(k = 1 \; to \; K) \;\; fk(x) \tag{2}$$

The prediction of the kth decision tree is denoted as $fk(x)$, and K is the total number of DT in the ensemble. Predictions are based on weighted averages of the leaf values that each tree learns throughout training. The XGBoost model can anticipate x from a set of inputs by adding up the predictions of all the ensemble decision trees.

The hyperparameters for the XGBoost model that has been suggested are as follows: 0.8 for the subsample ratio, 0.01% for the learning rate, a maximum depth of 6, 200 for the number of estimators, and 0.8 for collapse by tree. These tuned parameters help improve model performance and reduce overfitting. This setup is designed to achieve better generalization for correctly classifying tuberculosis.

G. *Evaluation metrics*

A classification model's overall performance may be shown in a confusion matrix, which is a tabular representation. The forecasts are split into four distinct groups: FP, TN, TP and TP. This comprehensive assessment determines how well the model performs and where it may be improved by testing its capacity to accurately classify instances across several classifications.

- True Positive: This event's occurrences that the model verified as favorable.
- True Negative: Situations that the model correctly classified as unfavorable.
- False Positive: Event where the model made a false positive classification.
- False Negative: Events that the model erroneously deemed to be negative:

Accuracy: A measure of how well the learned model can guess the number of input samples out of all the instances in the collection. This may be expressed as (3)-

$$Accuracy = \frac{\text{TP+TN}}{\text{TP+Fp+TN+FN}} \tag{3}$$

Precision: Prediction accuracy correlation coefficient (ACC) is the ratio of true positives to total positives for a given model. ACC displays. An example of a precision representation would be (4)-

$$Precision = \frac{\text{TP}}{\text{TP+FP}} \tag{4}$$

Recall: This statistic represents the total number of instances that should have been positive divided by the proportion of correctly anticipated positive events. It may be expressed mathematically as (5)-

$$Recall = \frac{\text{TP}}{TP+FN} \tag{5}$$

F1 score: The combination of recall and ACC strikes a balance between the two, making it a harmonic mean. It can take values between 0 and 1. According to the formula (6)-

$$F1 - score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{6}$$

Receiver Operating Characteristic Curve (ROC): A ROC curve shows the relationship between a set of classification criteria and the related FPR and TPR. The FPR is one definition of specificity, whereas the TPR is another name for sensitivity or REC.

IV. RESULTS AND DISCUSSION

The experimental setup is detailed below, and the suggested model's performance in the training and testing stages is highlighted to show how well it works. Using a Windows 10 PC with a 2.21 GHz Intel Core i7-6560U and 16 GB of RAM, I ran the tests. Python 3.12.7 and the PyTorch DL framework were utilized for each and every experiment. Finds a summary of the proposed XGBoost model's training and evaluation on the TBX11K dataset in Table II. The model was tested using important performance measures such as REC, ACC, PRE, and F1. ACC, PRE, REC, and F1 of 99.71% on the testing dataset show that the suggested model is successful, according to the experimental findings. These high scores demonstrate strong generalization on TB versus normal chest radiographs, strong prediction capabilities, and excellent classification abilities.

TABLE II. CLASSIFICTION RESULTS OF PROPOSED MODEL FOR TUBERCULOSIS DETECTION USING CHEST RADIOGRAPHS

Matrix	Testing	Training
Accuracy	99.71	100
Precision	99.70	100
Recall	99.74	100
F1-score	99.60	100

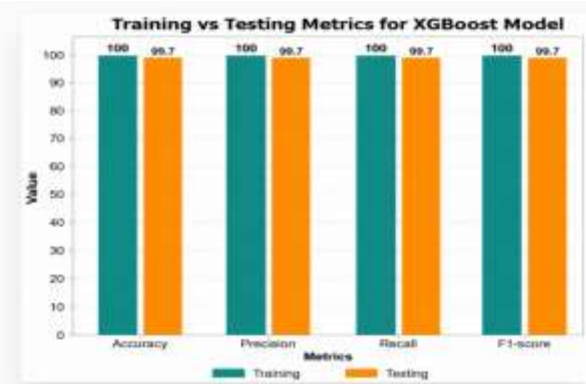

Fig. 7. Train and Test performance comparison of proposed XGBoost model for Tuberculosis Detection

Testing and training of the suggested XGBoost model for tuberculosis diagnosis using chest radiographs was shown in Fig. 7. Training metrics for ACC, PRE, REC, and F1 were 100%, while testing metrics for these measures were 99.71%, showing that the model performed very well and had great generalizability and dependable classification performance on new data.

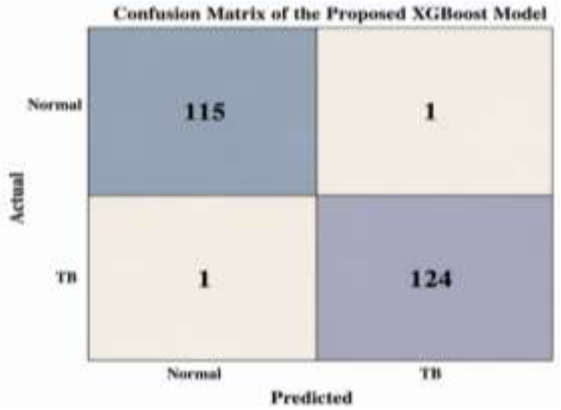

Fig. 8. Confusion Matrix for the XGBoost Model

The confusion matrix for TB detection using the XGBoost model is shown in Fig 8. The model correctly classified 115 Normal and 124 TB chest radiographs, with only one misclassification in each class, demonstrating excellent discrimination capability and high classification ACC for both Normal and TB cases.

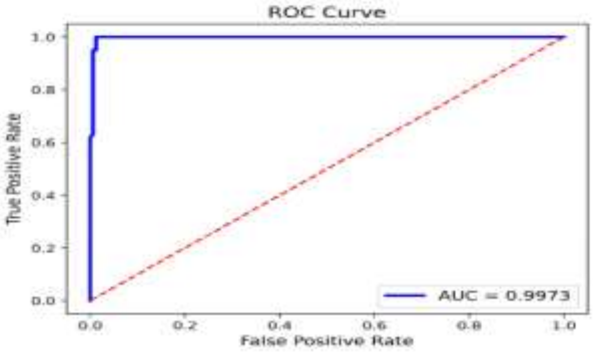

Fig. 9. ROC Curve for XGBoost model

The suggested XGBoost model for tuberculosis diagnosis has a ROC curve, which is shown in Fig 9. The AUC is 0.9973, which means that the curve closely follows the upper-left corner of the plot and has good discriminative power. It clearly distinguishes Normal from TB chest radiographs with a very low FPR.

A. *Comparative Analysis*

Table III shows that comparing the proposed model's ACC to that of other current models is one way to evaluate its effectiveness. The findings show that the suggested XGBoost model achieves a higher ACC, PRE, REC, and F1 of 99.71% compared to the DL and ML methods. The accuracies of these three networks were far lower than ResNet50, VGG16, and MobileNet-V2, coming in at 82.7%, 94.7%, and 90.1% respectively. These findings demonstrate the better image classification capabilities and high reliability of the proposed XGBoost model for tuberculosis detection from chest radiographs.

TABLE III. COMPARISON OF DIFFERENT MACHINE LEARNING AND DEEP LEARNING MODELS FOR TUBERCULOSIS DETECTION

Model	Accuracy	Precision	Recall	F1-score
ResNet50[25]	82.7	79.5	88.6	83.8
VGG16[26]	94.7	95.9	96.2	-
MobileNet-V2[27]	90.1	90.2	90.1	90.1
XGBoost	99.71	99.70	99.74	99.60

The proposed XGBoost model shows several merits such as high classification ACC, efficient learning and good generalization ability. The model has achieved 99.71% ACC, PRE, 99.70% recall and F1 in differentiating TB and normal chest radiographs with very low misclassifications and computational efficiency, giving reliable computer-aided diagnosis (CAD).

V. CONCLUSION AND FUTURE STUDY

Tuberculosis (TB) abnormalities can look similar to other pulmonary illnesses and can vary in appearance, making it difficult to diagnose TB on chest radiographs. In this study, a ML system was developed to automatically detect TB in preprocessed, balanced chest X-ray images using the XGBoost classifier. The proposed model achieved remarkable values of 99.71% for ACC, PRE, REC and F1. A comparative analysis indicated that XGBoost provides better classification ability as compared to ResNet50 (82.7%), MobileNet-V2 (90.1%) and VGG16 (94.7%). These results support the validity of the ACC and the efficiency of the proposed approach for large-scale screening and early screening for TB. The model could not be applied to other types of clinical settings due to the fact that only one benchmark dataset (TBX11K) was used. In addition, the XGBoost model proposed in this paper has good performance, but needs further validation in multi-center and real-world datasets. Integrating more and more varied datasets, making models more resilient, and investigating lightweight, real-time deployment methodologies for real-world clinical applications will be the primary goals of future research.

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