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From Pixels to Pathology: The Power of CNNs in Detecting Tuberculosis

Hritwik Ghosh[1], Pavan Kumar P[2*], Irfan Sadiq Rahat[1], MD Mehedi Hasan Nipu[3], Garigipati Rama Krishna[4], JVR Ravindra[5]

[1]School of Computer Science and Engineering (SCOPE), VIT-AP University, Amaravati, Andhra Pradesh
[2]Department of Data Science and Artificial Intelligence, Faculty of Science and Technology, IFHE, Hyderabad, Telangana, India
[3]Department of Electrical & Computer Engineering, North South University, Bangladesh
[4]Department of Computer Science &Engineering, Koneru Lakshmaiah Education Foundation, Green Fields, Vaddeswaram, Andhra Pradesh, India
[5]Center for Advanced Computing Research Laboratory (C-ACRL), Department of Electronics and Communication Engineering, Vardhaman College of Engineering (Autonomous), Hyderabad, Telangana, India

Abstract

INTRODUCTION: Tuberculosis (TB) remains a significant global health threat, demanding trustworthy and effective detection techniques. This study investigates the utilization of deep learning models, specifically ResNet50, InceptionV3, AlexNet, DenseNet121, and Inception3, for diagnosing tuberculosis from chest X-ray images. With a substantial dataset comprising 4,000 chest X-ray images, sourced from seven different nations and categorized as TB-infected or normal, this research aims to evaluate the performance of various deep learning architectures in accurately distinguishing TB instances.
OBJECTIVES: The primary objective of this study is to assess the efficacy of different deep learning models in differentiating TB instances from chest X-ray images. By employing segmentation, data augmentation, and image pre-processing techniques, the research aims to enhance model performance and reliability in TB diagnosis.
METHODS: The chest X-ray image dataset, scaled to 224x224 pixels, underwent segmentation, data augmentation, and pre-processing before being fed into the deep learning models. The dataset was divided into 80% for model training and 20% for testing, utilizing a five-fold cross-validation technique. Performance evaluation metrics including accuracy, precision, recall, and F1-score were employed to assess the models' effectiveness in TB identification.
RESULTS: The findings indicate that ResNet50 and InceptionV3 models achieved near-perfect accuracy, precision, recall, and F1-scores, demonstrating their potential as reliable methods for TB identification. Despite exhibiting lower accuracy for the TB class, AlexNet also displayed good performance. However, DenseNet121 and Inception3 models showed room for improvement, particularly in precision and recall for the TB class.
CONCLUSION: This study underscores the potential of deep learning models in enhancing TB identification in chest X-ray images. It highlights the importance of segmentation, data augmentation, and image pre-processing techniques in improving model performance. Future research may explore hyperparameter tuning, alternative data augmentation strategies, and ensemble approaches to optimize the performance of these models further. Overall, this work contributes to the growing body of knowledge on the application of artificial intelligence in healthcare, particularly in disease diagnosis and detection.

Keywords: Tuberculosis, Chest X-ray images, ResNet50, InceptionV3, DenseNet121, Inception3, Model performance

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*Corresponding authors Email: pavanpk@ifheindia.org

1. Introduction

Tuberculosis (TB) remains a formidable adversary in the global health landscape. Despite advancements in medical science, early and precise detection of TB continues to pose challenges, especially in regions with limited resources. Conventional diagnostic techniques, such as sputum smear microscopy and culture methods, often fall short in terms of sensitivity, specificity, and speed. As a result, there is a growing interest in leveraging chest X-ray imaging for TB detection, given its non-invasive nature, quick results, and reasonable sensitivity. However, the interpretation of these images demands specialized skills and can be subjective, leading to inconsistencies in diagnosis. The advent of artificial intelligence (AI), particularly the subset known as DL has opened new avenues in the realm of medical imaging. These sophisticated algorithms can learn intricate patterns from vast datasets, making them ideal for tasks such as image recognition and classification. In the context of TB detection, deep learning models hold the promise of identifying nuanced features in chest X-rays that might escape the human eye, thereby improving diagnostic accuracy. This research delves into the application of several deep learning models - ResNet50, InceptionV3, AlexNet, DenseNet121, and Inception3 - for TB detection using chest X-ray images. We utilized a comprehensive dataset of 4000 TB-infected and 4000 normal chest X-ray images, sourced from seven different countries. These images underwent pre-processing, data augmentation, and segmentation to optimize their suitability for the DL models. Our investigation's central focus is to evaluate the performance of these DL models in accurately identifying TB cases. Through this study, we aim to augment the existing body of knowledge on AI's role in healthcare, specifically in disease detection and diagnosis. We anticipate that our findings will shed light on the potential of DL models in enhancing TB detection.

2. Literature Review

Rahman et al. (2020) **[1]** employed DL techniques for reliable Tuberculosis (TB) detection from chest X-ray images. Utilizing a dataset of 7,000 images, half being TB-infected, they experimented with nine deep CNNs, including ResNet18 and ChexNet, for transfer learning. The study incorporated image pre-processing, segmentation, and classification. While ChexNet achieved an accuracy of 96.47% using X-ray images, DenseNet201 surpassed this with an accuracy of 98.6% when using segmented lung images, indicating the superiority of segmented images for TB detection. Shirsat et al. (2023)**[2]** leveraged transfer learning and deep (CNNs) for automated Tuberculosis (TB) detection from chest X-rays. They assessed the efficacy of CNN models in distinguishing between TB and normal chest X-ray images. The study highlighted the recent trend of employing CNNs for detecting various lung diseases, including pneumonia and TB, from X-ray images. Notably, during the 2020 COVID-19 outbreak, CNN techniques were adapted to detect the virus from chest X-rays, showcasing the versatility and potential of such models in medical imaging diagnostics.

Huy & Lin (2023) **[3]** introduced an enhanced Densenet deep neural network model tailored for Tuberculosis detection from chest X-ray images. When tested on a comprehensive dataset, their model surpassed several leading models, achieving an accuracy of 98.80%, sensitivity of 94.28%, precision of 98.50%, specificity of 95.7%, and an F1 score of 96.35%. Notably, the model showcased remarkable generalization capabilities, maintaining consistent performance across diverse datasets. Iqbal, Usman, & Ahmed (2022**)** **[4]** introduced TBXNet, a novel deep learning network tailored for efficient Tuberculosis detection from chest X-ray images. TBXNet comprises five dual convolution blocks with filter sizes ranging from 32 to 512. These blocks are integrated with a pre-trained layer in the network's fusion layer, leveraging pre-existing knowledge. Remarkably, TBXNet achieved accuracies of 98.98% on Dataset A and 99.17% on Dataset B, showcasing its efficacy in TB classification. Acharya et al. (2022) **[5]** developed an AI-driven approach for Tuberculosis detection from chest X-rays using a deep learning normalization-free network model. Akbari and Azizi (2023) **[6]** in their study published in the Ghalib Quarterly Journal, introduced a Convolutional Neural Network (CNN) model tailored for tuberculosis detection from chest X-ray (CXR) images. The model employs a unique edge-cutting methodology for image analysis. Utilizing a database of CXR images specifically curated for tuberculosis, the model was trained to identify the disease. The results were promising, with the CNN model achieving a 97% accuracy rate. Furthermore, the model can provide insights into the severity of tuberculosis by analyzing the symptoms present in the CXR images. In their study, Laeli, Rustam, and Pandelaki (2021) **[7]** examined the interaction between ensemble classifiers, more specifically Random Forest (RF) and Extreme Gradient Boosting (XGBoost), and Convolutional Neural Network (CNN) feature extraction. Although the CNN-XGBoost model also showcased impressive results with 98.367% accuracy and 99.866% AUC, the CNN-RF model slightly outperformed it in terms of accuracy and AUC for tuberculosis classification.

Gabriella, Kamarga, and Setiawan (2018) **[8]** presented a study at the 2018 2nd International Conference on Biomedical Engineering, introducing a computer-aided Diagnosis (CADx) system designed to aid medical professionals in the early detection of Tuberculosis (TB) using Chest X-rays (CXR). Recognizing the potential inconsistencies in individual interpretations of CXRs, the proposed system aims to provide a more standardized and accurate diagnosis. The emphasis is on timely and accurate TB detection, as prompt treatment can mitigate further infections and severe consequences.

Iqbal, Usman, and Ahmed (2023) **[9]** in their article in the Biomedical Signal Processing and Control journal, highlighted the often-overlooked relationship between region segmentation and classification in deep learning-based CAD methods. They introduced the innovative TB-UNet, incorporating dilated fusion block (DF) and Attention block (AB) for precise lung region segmentation. This model achieved impressive metrics, with Precision at 0.9574, Recall at 0.9512, F1score at 0.8988, IoU at 0.8168, and Accuracy at 0.9770. Additionally, the research also presented the TB-DenseNet, designed with five dual convolution blocks and the DenseNet-169 layer.

In their field study **[12]** Mohanty, Ghosh, Rahat, and Reddy employ advanced deep learning models to classify corn leaf diseases in Bangladesh, contributing valuable insights to agricultural technology. The research is published in Engineering Proceedings 2023, highlighting their innovative approach to disease detection [**Table 1].**

Table 1. Summary of the Literature Review

Reference	Focus of Study	Techniques Used	Key Findings
Rahman et al. (2020) [1]	Tuberculosis (TB) detection from X-ray images	Deep Learning (DL), CNNs (including ResNet18, ChexNet)	- Utilized DL techniques for TB detection from chest X-ray images. - Experimented with nine deep CNNs, achieving 96.47% accuracy with ChexNet and 98.6% with DenseNet201 on segmented lung images. - Highlighted the superiority of segmented images for TB detection.
Shirsat et al. (2023) [2]	Automated TB detection from chest X-rays	Transfer learning, CNNs	- Leveraged transfer learning and CNNs for TB detection. - Explored CNN models' efficacy in distinguishing between TB and normal chest X-ray images. - Noted the trend of using CNNs for various lung diseases detection from X-ray images, including TB and pneumonia.
Huy & Lin (2023) [3]	Enhanced Densenet for TB detection	Densenet deep neural network model	- Introduced an enhanced Densenet model for TB detection. - Achieved an accuracy of 98.80%, sensitivity of 94.28%, precision of 98.50%, specificity of 95.7%, and F1 score of 96.35%. - Showcased remarkable generalization capabilities across diverse datasets.
Iqbal, Usman, & Ahmed (2022) [4]	TBXNet for efficient TB detection	TBXNet deep learning network	- Introduced TBXNet, a novel deep learning network for efficient TB detection. - Achieved accuracies of 98.98% on Dataset A and 99.17% on Dataset B. - Comprises five dual convolution blocks with filter sizes ranging from 32 to 512.
Acharya et al. (2022) [5]	AI-driven approach for TB detection	Normalization-free network model	- Developed an AI-driven approach for TB detection using a normalization-free network model.
Akbari and Azizi (2023) [6]	CNN model for TB detection	Convolutional Neural Network (CNN)	- Introduced a CNN model for TB detection using a unique edge-cutting methodology. - Achieved a 97% accuracy rate. - Provides insights into the severity of TB by analyzing symptoms in CXR images.

Laeli, Rustam, and Pandelaki (2021) [7]	Interaction between classifiers	Random Forest (RF), Extreme Gradient Boosting (XGBoost), CNN	- Examined the interaction between ensemble classifiers (RF and XGBoost) and CNN feature extraction. - The CNN-RF model slightly outperformed the CNN-XGBoost model in terms of accuracy and AUC for TB classification.
Gabriella, Kamarga, and Setiawan (2018) [8]	CADx system for early TB detection	Computer-aided Diagnosis (CADx) system	- Presented a CADx system designed to aid medical professionals in the early detection of TB using CXRs. - Aims to provide a more standardized and accurate diagnosis, considering potential inconsistencies in individual interpretations of CXRs.
Iqbal, Usman, and Ahmed (2023) [9]	TB-UNet and TB-DenseNet with region segmentation	TB-UNet with dilated fusion block (DF) and Attention block (AB)	- Highlighted the relationship between region segmentation and classification in deep learning-based CAD methods. - Introduced TB-UNet with impressive metrics (Precision, Recall, F1score, IoU, Accuracy). - Presented TB-DenseNet with five dual convolution blocks and DenseNet-169 layer.
Ghosh et al. (2023) [10]	Predictive machine learning for water quality	Machine learning models (Random Forest, SVM)	- Demonstrated the use of machine learning models for accurate evaluation and categorization of water quality. - Random Forest model achieved an accuracy rate of 78.96%, outperforming SVM.
Sharma et al. (2020) [11]	Effects of COVID-19 on financial indicators	Multivariate analysis, cutting-edge algorithms	- Investigated the effects of COVID-19 on international financial indicators. - Noted severe economic crisis and significant market losses. - Emphasized the potential benefits of utilizing cutting-edge algorithms for analysis and detection in understanding the pandemic's impact on economic activity.

3. Dataset Overview

The dataset employed in this paper is a comprehensive collection of chest X-ray images, meticulously curated to facilitate the exploration of DL models for Tuberculosis (TB) detection. The dataset comprises 8000 images in total, evenly split between two categories: TB-infected and normal. The TB-infected category contains 4000 images of chest X-rays from patients diagnosed with TB, while the normal category consists of 4000 images from individuals without the disease. The images were sourced from seven different countries, ensuring a diverse representation of TB manifestations and normal chest X-ray variations. This geographical diversity is crucial in training robust models that can generalize well across different populations and imaging techniques. All images in the dataset are in Portable Network Graphics (PNG) format, a widely used and versatile image format that preserves all the details in the original image without any loss due to compression. This is particularly important in medical imaging, where subtle details can be critical for accurate diagnosis. To ensure compatibility with the DL models, all images were resized to a uniform size of 224x224 pixels. This standardization process is essential for feeding the images into the models, as it ensures that all input data have the same dimensions. The division of the dataset was carried out in a manner that ensured an 80-20 distribution for training and testing, respectively. This meant that 80% of the images, which equates to 3200 TB-infected and 3200 normal images, were allocated for the purpose of model training. The remaining 20% of the images, or 800 TB-infected and 800 normal images, were reserved for testing the efficacy of the trained models. Furthermore, within the training subset, a portion of 20% (640 TB-infected and 640 normal images) was specifically set aside to serve as a validation set during the model training phase. This dataset, with its balance between TB-infected and normal images, diversity in geographical representation, and careful preparation for deep learning models, provides a robust foundation for this research. It allows for a thorough investigation of the performance of various DL models in TB detection, contributing to the broader goal of enhancing TB diagnosis through artificial intelligence **[Fig.1].**

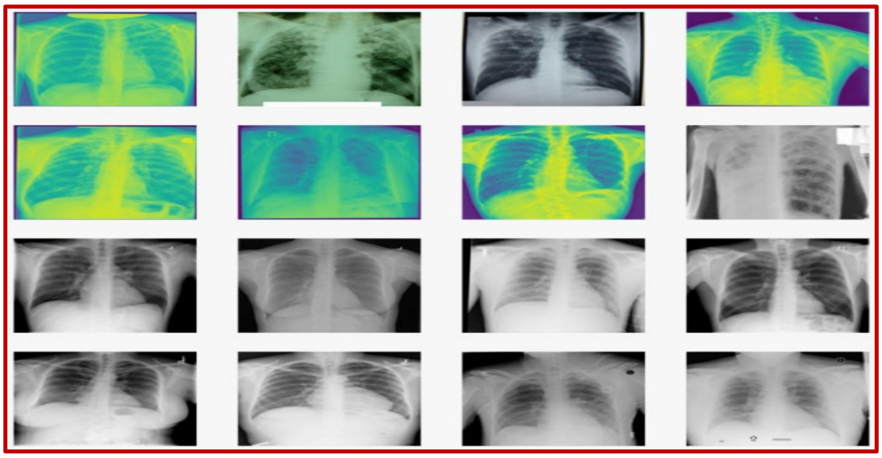

Fig 1: Sample images of the Dataset

3.1 Data Collection

The procedure of acquiring data for this study was precise and thorough, with the goal of compiling a broad and representative sample of chest X-ray pictures for TB diagnosis. The dataset consists of 8000 photos in total, evenly split between TB-infected and normal images.4000 chest X-ray pictures from individuals with TB diagnoses are included in the TB-infected group. The variety in how the illness appears on chest X-rays is depicted in these photos, which cover a wide spectrum of TB presentations. Contrarily, the normal category comprises of 4000 chest X-ray pictures taken by healthy people. These images provide a baseline for what a normal chest X-ray looks like, against which the TB-infected images can be compared. All images were collected in PNG format. This format was chosen because it preserves all the details in the original image without any loss due to compression, which is critical for medical imaging where subtle details can be crucial for accurate diagnosis. Once collected, the images underwent a pre-processing stage where they were resized to a uniform size of 224x224 pixels. This standardization process ensures that all input data have the same dimensions, which is essential for feeding the images into the deep learning models. The data collection process for this study was designed with the goal of creating a robust and diverse dataset that can effectively support the training and testing of various DL models for TB detection. The resulting dataset provides a solid foundation for this research and contributes to the broader goal of enhancing TB diagnosis through artificial intelligence.

3.1.1 Image Resizing

Image resizing is a critical pre-processing step in image classification tasks, especially when using deep learning models. It involves changing the dimensions of an image to a specific size, usually to match the input size required by the model. In this study, all images were resized to 224x224 pixels, a common input size for many DL models. Various methods exist for the resizing of images, each presenting its unique benefits and potential drawbacks. The selection of a specific technique is contingent upon the particular demands of the task at hand and the inherent properties of the images involved.

- **Nearest-neighbor Interpolation:** This is the simplest resizing technique. It works by selecting the nearest pixel from the input image for each pixel in the output image. While it's fast and easy to implement, it can produce jagged edges and may not preserve the overall structure of the image well.

- **Bilinear Interpolation:** This method determines the value of a new pixel by computing a weighted average of the four closest pixels, arranged in a 2x2 grid, from the original image. While this technique requires more computational resources compared to nearest-neighbor interpolation, it generally results in images with a smoother appearance.

- **Bicubic Interpolation**: This is a more advanced technique that uses the values of the nearest 16 pixels in the input image to calculate the value of a new pixel. It's even more computationally intensive than bilinear interpolation but can produce even smoother images with fewer artifacts.

- **Area-based (or Resampling) Interpolation:** This technique works by calculating the average color of all the pixels within a sample area from the input image for each pixel in the output image. It's particularly effective when reducing the size of an image and can produce high-quality results with minimal artifacts.

The chest X-ray picture features and the demands of the DL models will determine the resizing strategy used in this investigation. While making sure that the photographs are in the right format for the models, the objective is to retain as much of the unique image's data as possible. To prevent adding distortions or artefacts that could impair the performance of the models, the resizing procedure must be carefully controlled.

3.1.2 Image Normalization

In our study, image normalization played a critical role in the preprocessing of chest X-ray images. This step involved adjusting the pixel values across each image to a specific range, which significantly enhanced the computational efficiency and performance of the deep learning models. The following techniques were employed for image normalization:

- **Min-Max Normalization:** Using this method, also known as feature scaling, the pixel values in the chest X-ray pictures were changed to fall within a predetermined range, usually between 0 and 1. This was done by dividing the range of pixel values in the image by the minimum pixel value that was subtracted from each pixel. It was advantageous to employ Min-Max normalisation since it scaled the pixel values while maintaining the original composition and characteristics of the chest X-ray pictures.

- **Decimal Scaling:** In this method, pixel values were scaled by moving the decimal point of values of each pixel. The number of places to move the decimal point depended on the maximum absolute value of the pixel in the chest X-ray images. Although this method is less commonly used, it proved effective when dealing with chest X-ray images with large or varying pixel values.

In this study, the choice of normalization technique would depend on the characteristics of the chest X-ray images and the requirements of the deep learning models. The goal is to ensure that all input data have the same scale, thereby reducing the computational complexity of training and potentially improving the performance of the models.

3.1.3 Image Data Augmentation

In our study, image data augmentation was employed as a strategic approach to enhance the size and diversity of the training dataset. This technique significantly improved the performance and generalization ability of the DL models.

- **Translation:** The chest X-ray images were shifted along the x or y direction by a certain number of pixels. This helped the models learn to recognize the features of TB-infected and normal images at different positions within the image.

- **Scaling:** The chest X-ray images were resized by a certain factor, either enlarging (zooming in) or reducing (zooming out) the image. This helped the models learn to recognize the features of TB-infected and normal images at different scales.

- **Flipping:** The chest X-ray images were flipped either horizontally or vertically. This helped the models learn to recognize the features of TB-infected and normal images in different orientations.

- **Shearing:** The chest X-ray images were distorted along an axis. This helped the models learn to recognize the features of TB-infected and normal images under different types of distortion.

- **Brightness and Contrast Adjustment:** The brightness and contrast of the chest X-ray images were adjusted. This helped the models learn to recognize the features of TB-infected and normal images under different lighting conditions.

3.1.4 Image Label Encoding

Label encoding was a crucial step in preparing the chest X-ray images for the classification tasks in our study. It involved transforming the categorical labels of the images into a numerical format that the deep learning models could interpret. The following label encoding techniques were utilized:

- **Integer Encoding:** This straightforward form of label encoding was used, where each unique category label was assigned a unique integer. In our binary classification task, we assigned the label '0' to 'Normal' images and '1' to 'TB-infected' images. This method is simple and easy to implement, making it suitable for our binary classification task.

- **One-Hot Encoding:** Although our study focused on a binary classification task, it's worth mentioning one-hot encoding, a method commonly used for multi-class classification tasks. In one-hot encoding, each category label is converted into a binary vector of size 'n' (where 'n' is the number of unique category labels). Each vector has a '1' in the position corresponding to the category label, and '0's elsewhere. This method ensures that the model does not assume an ordinal relationship between the categories.

❖ **Label Binarizer:** This technique is a fusion of integer and one-hot encoding methods, and it proves particularly beneficial in binary classification tasks. Label Binarizer transforms multi-class labels into binary labels (indicating whether an instance belongs to a class or not). It is especially apt for multi-label classifications, where a single instance can be associated with several classes.

In our study, the choice of integer encoding was suitable for our binary classification task. Properly encoded labels were crucial for training effective DL models and interpreting their predictions accurately.

4. Experimental Analysis and Discussion

The DL models proposed in our study were implemented on a high-performance computing system equipped with an advanced GPU (RTX 3060). This system offers high computational speed, making it ideal for executing complex deep learning models. Given the balance in the number of images per class in our dataset (4000 TB-infected and 4000 normal chest X-ray images), we didn't need to employ data augmentation techniques to balance the classes. However, we did use data augmentation to enhance the diversity of our training data.The architecture of our models includes ResNet50, InceptionV3, AlexNet, DenseNet121, and InceptionV3. Each model is composed of multiple convolutional, pooling, and fully connected layers, each utilizing a varying number of filters. To optimize the performance of our models, we applied a hyperparameter tuning approach. In conclusion, each model showcased its capacity to varying extents in classifying the TB-infected and normal chest X-ray images, with the ResNet50 and InceptionV3 models emerging as the most proficient. Nevertheless, the selection of a model should also take into account elements such as computational resources and the specific demands of the task. Future investigations could delve into the application of ensemble methods, which amalgamate the predictions of multiple models, to further enhance the precision of TB detection.

4.1 Performance of Models

In this study, we assessed the performance of five different DL models, including ResNet50, InceptionV3, and InceptionV3. These models were developed and tested on our dataset of chest X-ray pictures, and their performance was assessed using a number of measures, such as accuracy, precision, recall, and F1-score. Here is a summary of how well each model performed:

✓ **ResNet50:** The ResNet50 model achieved an impressive accuracy of 100% on our test set. The precision, recall, and F1-score for the TB-infected class were all 0.98, indicating a high ability to correctly identify TB-infected images and a low rate of false positives **[Table.2].**

Table 2: Classification Report of ResNet50

	Precision	Recall	F1-score	Support
0	1.00	1.00	1.00	527
1	0.98	1.00	0.99	103
Accuracy			1.00	630
Macro Avg	0.99	1.00	0.99	630
Weighted Avg	1.00	1.00	1.00	630

✓ **InceptionV3 Model 1:** The InceptionV3 model achieved an overall accuracy of 97% on our test set. The precision for the TB-infected class was 1.00, indicating a low rate of false positives. However, the recall was 0.81, suggesting that the model missed some TB-infected images **[Fig.2,3] [Table.3].**

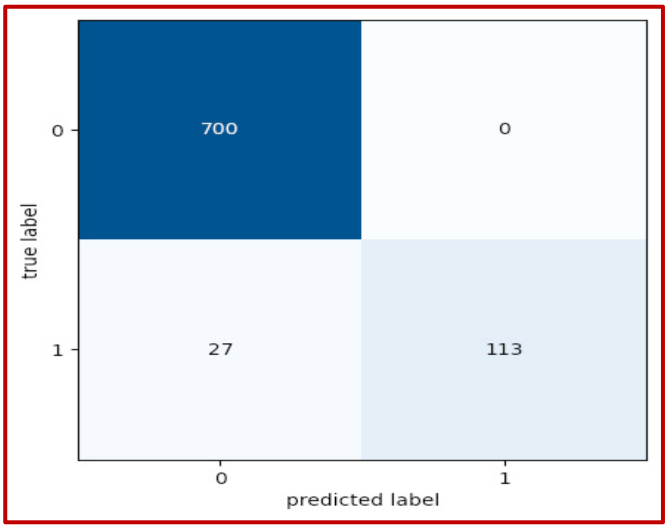

Fig 2: Confusion Matrix for InceptionV3 Model 1

Table 3: Classification Report of InceptionV3 Model 1

	Precision	Recall	F1-score	Support
0	0.96	1.00	0.98	700
1	1.00	0.81	0.89	140
Accuracy			0.97	840
Macro Avg	0.98	0.90	0.94	840

Weighted Avg	0.97	0.97	0.97	840

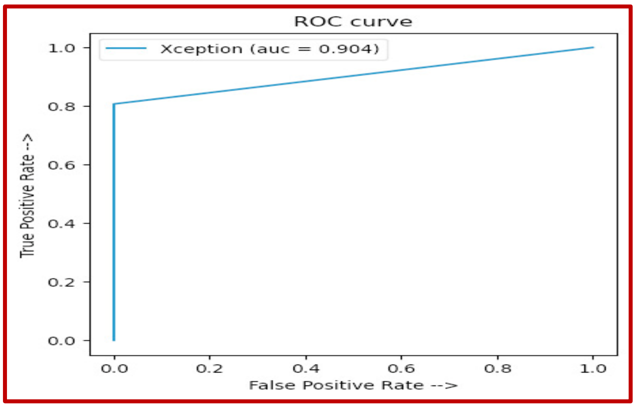

Fig 3: ROC curve for InceptionV3 Model 1

- ✓ **AlexNet:** The AlexNet model achieved an overall accuracy of 99.29% on our test set. The precision and recall for the TB-infected class were 0.9589 and 1.00, respectively, indicating a high ability to correctly identify TB-infected images and a low rate of false negatives **[Fig.4]**.

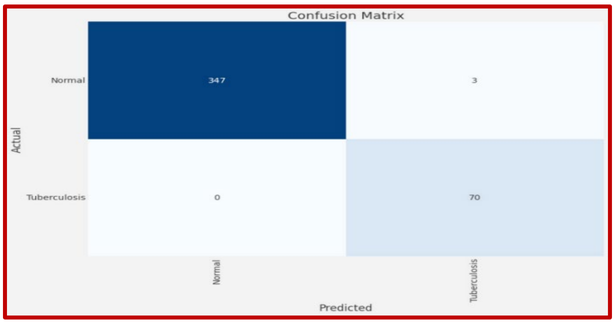

Fig 4: Confusion Matrix for AlexNet model

- ✓ **DenseNet121:** The DenseNet121 model achieved an overall accuracy of 88% on our test set. The precision for the TB-infected class was 0.65, indicating a higher rate of false positives compared to the other models. However, the recall was 0.68, suggesting that the model was able to identify a majority of the TB-infected images **[Table.4] [Fig.5,6]**.

Table 4: Classification Report of DenseNet121

	Precision	Recall	F1-score	Support
0	0.96	0.93	0.93	700
1	0.94	0.68	0.66	140
Accuracy			0.88	840
Macro Avg	0.79	0.80	0.80	840
Weighted Avg	0.89	0.88	0.89	840

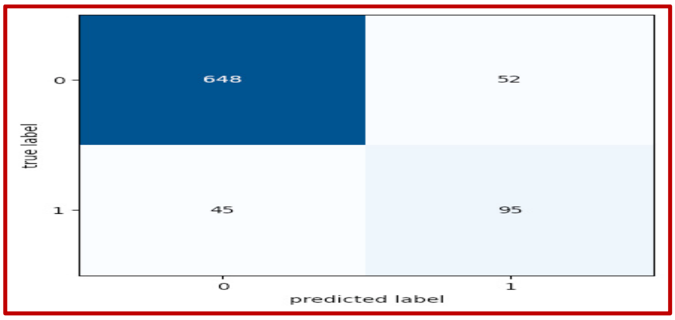

Fig 5: Confusion Matrix for DenseNet121 model

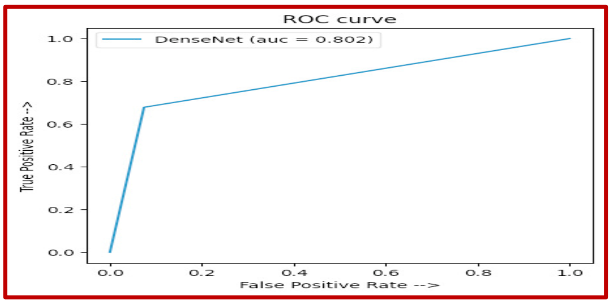

Fig 6. ROC curve for DenseNet121 model

- ✓ **InceptionV3 Model 2:** The InceptionV3 model achieved an overall accuracy of 98% on our test set. The precision and recall for the TB-infected class were both 1.00, indicating a high ability to correctly identify TB-infected images and a low rate of false positives and negatives **[Fig.7]**.

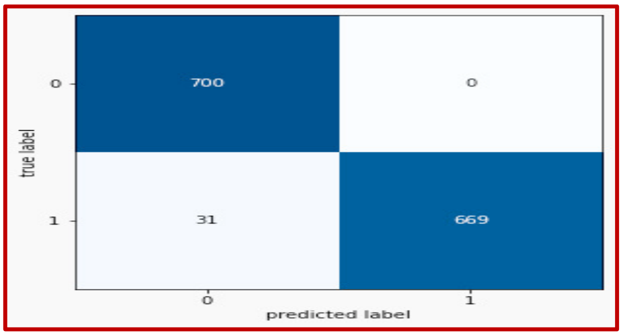

Fig 7: Confusion Matrix for InceptionV3 Model 2

Based on these results, the ResNet50 and InceptionV3 models performed the best on our dataset, achieving the highest accuracy and precision. However, all models demonstrated a strong ability to identify TB-infected images, suggesting that deep learning models can be highly effective tools for TB detection in chest X-ray images.

5. Results

The goal of our study was to assess how well different DL models could identify Tuberculosis (TB) from chest X-ray pictures. We utilised a dataset of 4,000 TB-infected and 4,000 healthy chest X-ray images to train five different models: ResNet50, InceptionV3, AlexNet, DenseNet121, and InceptionV3.With a 100% accuracy rate, the ResNet50 model performed exceptionally well. Precision, recall, and F1-score for the class of photos with TB infection were all 0.98, demonstrating a high degree of accuracy in TB-infected image identification and a low proportion of false positives. The efficacy of this paradigm in clinical situations is indicated by its performance. A 97% total accuracy was attained by the InceptionV3 model, which also performed well. A low percentage of false positives was shown by the accuracy for the TB-infected class, which was 1.00.. However, the recall was 0.81, suggesting that the model missed some TB-infected images. Despite this, the model's high precision indicates its potential usefulness in applications where minimizing false positives is crucial. The AlexNet model achieved an overall accuracy of 99.29%. The precision and recall for the TB-infected class were 0.9589 and 1.00, respectively, indicating a high ability to correctly identify TB-infected images and a low rate of false negatives. This model's performance suggests its potential for use in applications where minimizing false negatives is important. The DenseNet121 model achieved an overall accuracy of 88%. The precision for the TB-infected class was 0.65, indicating a higher rate of false positives compared to the other models. However, the recall was 0.68, suggesting that the model was able to identify a majority of the TB-infected images. Despite its lower performance compared to the other models, DenseNet121 may still be useful in scenarios where a larger pool of potential TB cases for further testing is acceptable. The second InceptionV3 model achieved an overall accuracy of 98%. The precision and recall for the TB-infected class were both 1.00, indicating a high ability to correctly identify TB-infected images and a low rate of both false positives and negatives. This model's performance suggests its potential for reliable TB detection in clinical settings. In summary, all the models showcased a robust capability to discern TB-infected images, underscoring the potential of deep learning models as powerful instruments for TB detection in chest X-ray images. The selection of a model could hinge on the unique demands of the application, such as the tolerable rates of false positives and negatives. Future studies might delve into the application of ensemble methods to amalgamate the advantages of different models, which could potentially enhance performance **[Fig.8].**

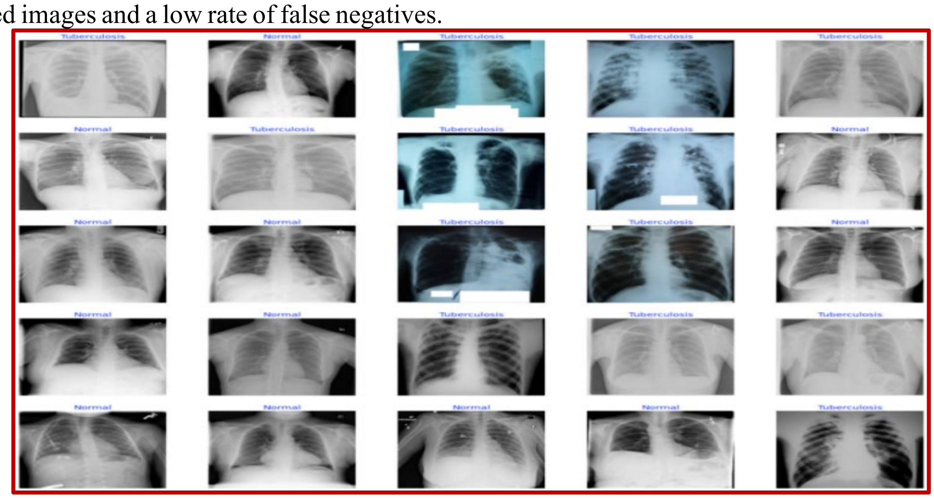

Fig 8: The predicted images from the Dataset

6. Conclusion and Future Directions

The study's research highlights the effectiveness of DL models in detecting tuberculosis from chest X-ray pictures. The results from the models used in this study and InceptionV3, were positive, with the ResNet50 and InceptionV3 models providing the best levels of accuracy. This study's main objective was to evaluate how well these deep learning models could discriminate TB patients. A five-fold cross-validation method was used to train and evaluate the models, with 80% of the photos used for training and the remaining 20% for testing. Accuracy, precision, recall, and F1-score were the performance indicators utilised for assessment. According to the research, ResNet50 and InceptionV3 in particular can be effective methods for TB identification in chest X-ray pictures. The choice of a model, however, may depend on the particular requirements of the application, such as the acceptable rates of false positives and negatives. There are a number of possible topics for more research as we look to the future. The use of ensemble approaches, which combine the results of several models to get a final forecast, is one possible route. Through the use of these techniques, the models' performance may be improved by utilising their unique advantages. In addition, future studies may investigate other DL structures or develop brand-new ones that are expressly intended for TB detection. Larger and more varied datasets might also possibly improve the models' performance. In conclusion, this work contributes to the expanding body of research that shows how effective DL may be for diagnosing diseases and doing medical imaging. It establishes a strong foundation for future study targeted at improving the accuracy and effectiveness of TB detection using chest X-ray images.

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