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Deep Learning-Based Tuberculosis Detection from Chest X-Ray Images

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Abstract- Due to a lack of technical improvements in diagnosis and treatment, tuberculosis (TB) continues to impact millions of people worldwide, despite the availability of highly effective medicines. Accurate identification and early diagnosis are crucial for reducing the spread and enhancing treatment results. Traditional diagnostic methods, such as sputum microscopy and culture, are labour-intensive and susceptible to human error since they are carried out by laboratory professionals. The field of deep learning (DL) has lately seen remarkable progress, and it shows great promise for improving and automating the accuracy of diagnoses. A DL-based approach to TB detection in chest X-rays is proposed in our work. Following training on a large dataset, our model outperforms traditional methods with a loss of 8.19 percent and an impressive accuracy of 97.32 percent. With convolutional neural networks (CNN) as its foundation and augmented with transfer learning (SqueezeNet) and explainable artificial intelligence (AI) methods like Grad-CAM, the model can accurately identify TB-related patterns while producing few false positives. More reliable, scalable, and rapid solutions for healthcare systems throughout the world may be possible with this approach, which would revolutionise TB diagnosis.

Keywords— Tuberculosis, Deep learning, Image augmentation, CNN, SqueezeNet

I. INTRODUCTION

Mycobacterium tuberculosis[1] produces tuberculosis (TB), which is a huge global health concern since it accounts for millions of new cases and deaths every year. Tuberculosis (TB) remains a major killer and disabler despite enormous strides in public health and medicine. This is especially true in developing and emerging countries where healthcare infrastructure is lacking. The traditional methods for diagnosing tuberculosis (TB) include taking X-rays of the chest and analysing sputum samples under the microscope [2]. Despite their significance, these approaches have disadvantages such as inconsistent diagnostic accuracy, high falsenegative rates, and inadequate sensitivity.

One revolutionary method for tackling these issues is deep learning, a potent branch of AI [3]. The advent of deep learning has revolutionised medical imaging by making complicated pattern detection in images more automated and accurate [4]. This holds truest when convolutional neural networks (CNNs) are used. New advancements in training convolutional neural networks (CNNs) to identify subtle but suggestive radiological markers that traditional approaches miss could make tuberculosis (TB) diagnosis easier. Treatment and prevention of tuberculosis (TB) are often within reach. However, tuberculosis (TB) was the second most infectious agent-related killer worldwide in 2022, with roughly twice as many deaths as HIV/AIDS [5]. The only other infectious agent-related killer was coronavirus disease (COVID-19). Over 10 million individuals a year are still affected by tuberculosis. Stopping the global tuberculosis (TB) epidemic by 2030 requires urgent action, according to all UN Member States and the WHO.

Deep convolutional neural networks (DCNs) such as SqueezeNet are effective and beneficial for image classification tasks, such as TB diagnosis from chest X-ray images [4]. Using highly connected layers helps with feature propagation and reduces overfitting. Trained on a tagged dataset, SqueezeNet employs an efficient method to detect TB-related patterns [7]. Then, we put Grad-CAM to work, which stands for Gradient-weighted class activation mapping, to highlight the X-ray [8] areas that are crucial for the model to achieve its goal. These portions are highlighted by Grad-CAM to make SqueezeNet's predictions easier to grasp. This computer enables accurate diagnosis, boosts physician trust in AI models [9], and comprehends categorisation reasoning.

The TB-Report of India (2024) reports that the tuberculosis death rate declined from 28 per 100,000 in 2015 to 23 per 100,000 in 2022. Now Trending

Regarding the cases of tuberculosis (TB) and deaths caused by it: Despite an uptick in private sector reporting, government health (GH) clinics continue to receive the vast majority of tuberculosis (TB) cases. Out of 25.5 lakh cases recorded in 2023, 8.4 lakh were attributed to private health groups, or around 33%. Up from 27.4 lakh in 2022, the expected tuberculosis incidence in 2023 was 27.8 lakh. India aims to have treated 95% of the sick population by 2023. India can end TB and guarantee a healthy future for its whole population by embracing a comprehensive, people-centered approach. Modern, state-of-the-art technology, such as artificial intelligence (AI)[10] and deep learning (DL)[11], will also make TB detection and diagnosis easier and faster.

Image processing methods were the primary emphasis of earlier work on computer-assisted tuberculosis (TB) diagnosis [12], with detection models using MATLAB and rudimentary convolutional neural network (CNN) [13]. Section 1 provides an overview of tuberculosis and its application in deep learning diagnosis; Section 2 provides examples of pertinent prior research; Section 3 details the proposed approach and its implementation; Section 4 presents the outcomes and experimental results; and Section 5, which concludes the work, includes a list of references.

What this endeavour has brought to the table: 1. Convolutional neural networks (CNNs) look at X-rays of the chest to find TB. 2. The SqueezeNet transfer learning method, which uses previously defined weights, improves the accuracy of the classification. 3. The GRADCAM approach, which is part of the Explainable AI (XAI) architecture, is utilised to make the result simpler to grasp and visualise.

II. RELATED WORKS

According to the following article: [2]: Early detection is crucial in halting the spread of tuberculosis (TB), reducing mortality rates, and protecting people from infection. However, the task at hand is rather challenging. As a result, researchers are struggling to develop a cost-effective and reliable computer-aided diagnostic (CAD) system for tuberculosis (TB) diagnosing.

In this research, we introduced a CAD device—a deep learning network that is both simple and effective—that can accurately classify a large number of TB CXR pictures. Five dual convolution blocks make up the network's core.

A serious infectious ailment affecting people all over the world, tuberculosis (TB) is caused by Mycobacterium tuberculosis, according to this research [3]. To diagnose this potentially deadly issue, a team of highly trained medical experts will require many hours of their time. By using the MobileNet transfer learning paradigm, this study suggests a computationally lightweight model. The optimal total accuracy, which may be attained with a computationally lightweight TL model, is 98.66%. We were able to achieve quicker convergence and better predictions than previous iterations of our model by reducing the number of trainable parameters. The fact that our method's weights are easily modifiable to fit new datasets is another perk.

Studies have shown that microscopic sputum smear images may be used independently to identify tuberculosis bacilli [14]. The World Health Organization (WHO) reports that TB is the tenth main cause of death worldwide. Traditional microscopic examination of a sputum smear is still the gold standard for tuberculosis diagnosis, however other procedures do exist. The conventional approach to diagnosis is time-consuming and error-prone, even when carried out by experts. They tested their method with 22 micrographs of sputum smears set against highdensity and low-density backgrounds, respectively. The final results show that the proposed algorithm for tuberculosis identification achieves a recall of 97.13%, a precision of 78.4%, and an F-score of 1986.766%.

Radiographs of the chest are an essential CAD tool for respiratory disorders as COVID-19, pneumonia, and TB because they show the anatomy of the chest accurately, as stated in this article [15]. However, many disorders can only be accurately diagnosed by sophisticated medical imaging equipment and skilled specialists via a time-consuming and difficult radiographic procedure. The results of our last experiment show that our knowledge distillation method beats existing DL algorithms for detecting respiratory illnesses in real-time, both in terms of processing complexity and performance. On average, our method obtains a recall of 0.97, an accuracy of 0.97, and a precision of 0.94.

III. PROPOSED METHODOLOGY

When applying deep learning for tuberculosis (TB) diagnosis, several crucial steps are often involved. Here is a quick rundown of what's involved: Figure 1 shows the block diagram of the proposed method.

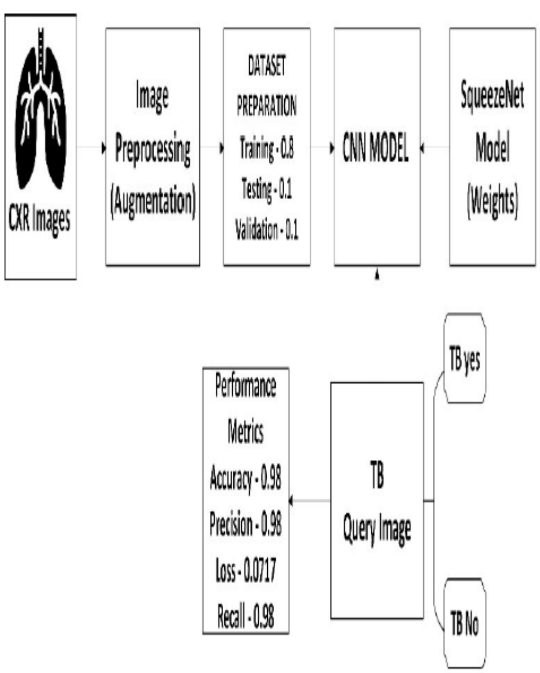

Fig.1. Proposed method Block diagram

Dataset Preparation

Documents and picture loading: first, XR images and the data associated with them were dispersed. The set includes both typical and tuberculosis-related CXR images. We were able to distinguish between healthy persons and tuberculosis patients since the data was pre-labeled. Pictures of normal cells and cells infected with TB are shown in Figure 2.

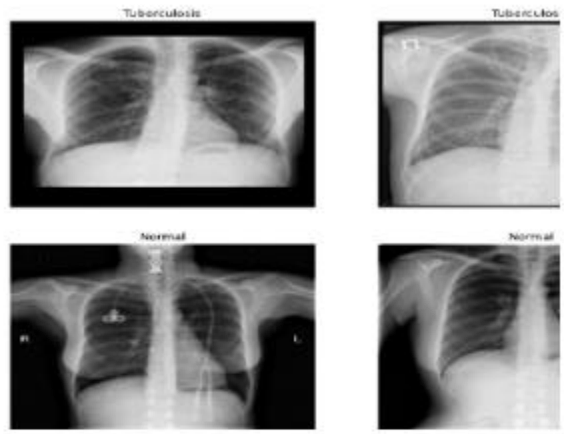

Fig.2. Sample Images of Infected and Uninfected cells

Data partitioning for use in testing, validation, and training: We separated the data into three groups to make sure the model would always perform the same. The training set is used for the purpose of training the model.

The validation set allows for hyperparameter tuning to avoid overfitting. The testing set is used to assess the model's ultimate performance. To divide the data into training and validation, an 80/20 split was used, and for testing, a 10/10 split was used. The training dataset includes the images seen above.

Preprocessing Data

Scaling, normalising, and improving the images using rotation, magnification, and flipping algorithms to boost generalisability were all necessary steps in integrating the images into the network architecture. A train generator required this to be built. A train generator was built to allow for fast training data input and on-the-fly preprocessing.

We constructed independent generators for the validation and test datasets and used them unchanged to preserve the assessment's dependability. The final product of the train generator's scaling operations. For quality assurance, they displayed a normalised training generator picture sample for preprocessing. To make the images suit the model's input form, we reduced their size and changed the pixel values from 0 to 1.

Figure 3 shows that the data distribution was skewed before the enhancement. and, after image enhancement, a normally distributed set of data (Figure 4).

The dataset was skewed because more images of regular X-rays were included than of tuberculosis. Class weighting, in which the frequencies of classes are inversely proportional to their weights, is one approach that was employed to deal with problem. Oversampling refers to enriching the data in order to increase the number of tuberculosis images. By reducing the model's inclination to choose the majority class, these strategies improved it. each class's relevance. Implementation of the loss function's sample weighting fix (which treats positive and negative losses equally).

To determine the ultimate weight reduction for use in transfer learning architecture, one may use the following formula:

$$L_{ce}^{y} = -(G_p . w . \log(f(x)) + G_n(1-w)\log(1-f(x) \quad (1)$$

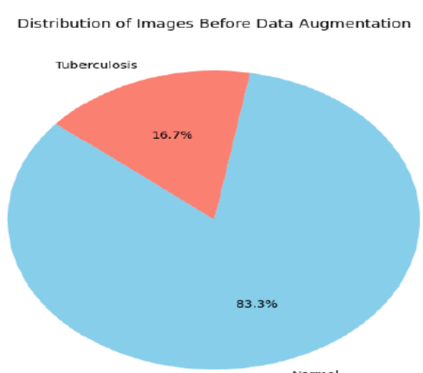

Fig.3. Imbalanced data distribution before Image Augmentation

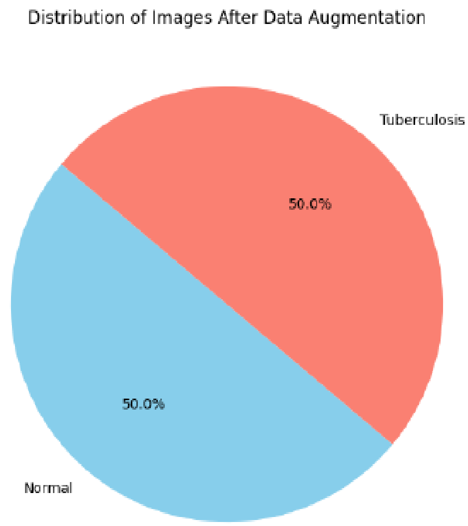

Fig.4. Balanced data distribution after Image Augmentation

Transfer learning

For transfer learning, one possible convolutional neural network (CNN) is SqueezeNet, which has been pre-trained on the ImageNet Dataset.

The model was able to accomplish quicker convergence and better accuracy with a reduced dataset by using pre-learned features. A brief overview of the model To improve squeezeNet's performance in binary classification (normal vs. TB), we added more layers into its design. The final layer of output used a sigmoid activation model to determine the probability of tuberculosis in the given X-ray. The SqueezeNet architecture classifies tuberculosis (TB) pictures using a highly compressed convolutional neural network (CNN) that is built on Fire modules. Prior to extending features using concurrent 1x1 and 3x3 convolutions, a 1x1 squeeze layer is used to reduce the number of input channels. By feeding SqueezeNet preprocessed chest X-ray pictures, the network effectively learns crucial TB-related characteristics like opacities, cavities, infiltrates, and textural abnormalities in the lung fields.

Assessing the Model

Following training, the model was evaluated using a number of metrics: Classification Report: The model's performance in classification was evaluated using metrics such as F1-score, recall, accuracy, and precision. Classification results showed promise with respect to TB diagnosis accuracy and false negative rate. To show that the model could differentiate between healthy and TB X-ray images, a confusion matrix was constructed. Quantities of accurate and incorrect positive/negative classifications were compared.

IV. RESULTS & DISCUSSION

The values of recall, f1-score, accuracy, and precision are shown in the classification report (Fig. 5).

Classification report:

```
              precision    recall  f1-score   support

      Normal       0.99      0.97      0.98       475
Tuberculosis       0.97      0.99      0.98       435

    accuracy                           0.98       910
   macro avg       0.98      0.98      0.98       910
weighted avg       0.98      0.98      0.98       910

Precision: 0.9727891156462585
Recall: 0.9862068965517241
F1-Score: 0.9794520547945206
```

Fig.5. Classification report of Classification

The Confusion Matrix (CM) that was created is seen in Figure 6.

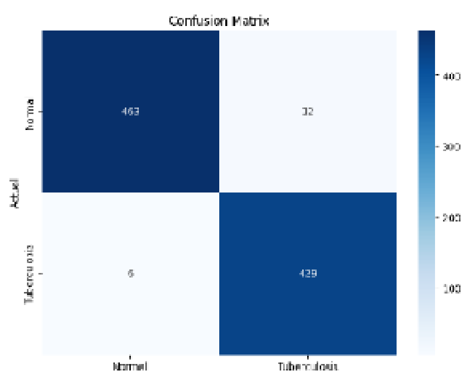

Fig.6. Confusion matrix of classification

The term "precision" is used to describe the ratio of the number of correctly classified true positives to the sum of all true positives and false positives.

$$\text{Precision} = \frac{TP}{TP + FP} = 0.98 \qquad (2)$$

Because it focuses only on the classification of positives, recall is more important than sensitivity in determining the DL model's potential to identify positive samples.

$$\text{Recall} = \frac{TP}{TP + FN} = 0.98 \qquad (3)$$

The F1 score is also known as the F measure. In order to strike a good balance between recall and accuracy, the model needs a large number of True Negatives and True Positives.

$$\text{F1 score} = \frac{2(Precision * Recall)}{Precision + Recall} = 0.98 \qquad (4)$$

The ratio of the number of true negative and positive classifications to the total number of instants is the accuracy metric.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} = 0.98 \qquad (5)$$

At epoch 20, as seen in Figure 7, CNN achieves an accuracy of 97.37 percent.

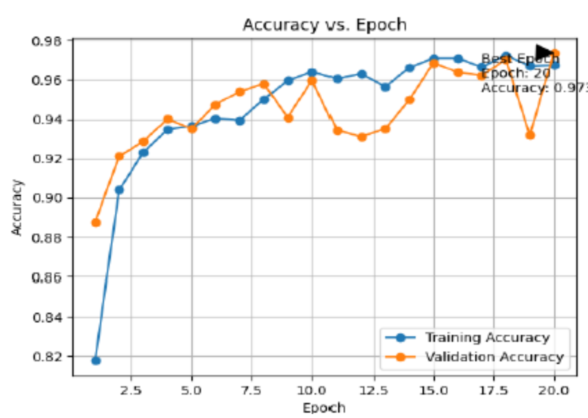

Fig.7. Plot of Accuracy vs. Epoch

At epoch 20, CNN produces a loss of 0.0869, as seen in Figure 8.

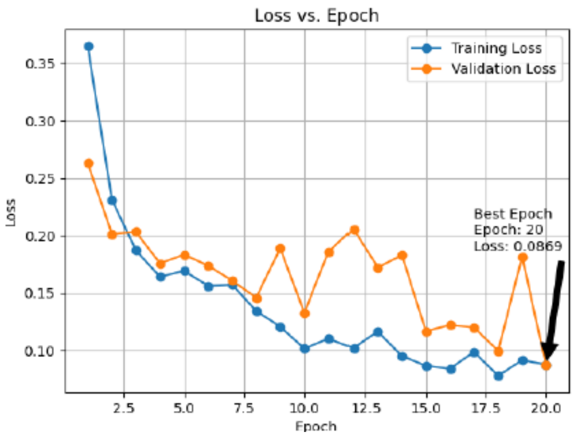

Fig.8. Plot of Loss vs. Epoch.

V. CONCLUSION

This article details the successful development of a deep learning model for tuberculosis detection in chest X-ray pictures using SqueezeNet. With the use of transfer learning, the model was able to achieve excellent recall and accuracy in distinguishing between normal and TB-affected lungs. A 97.37% accuracy rate and an 8.69% loss were the results of the model's enhanced performance, which was achieved via the application of data augmentation and class weighting to address the class imbalance. Plus, with the aid of Grad-CAM, we could understand the model's judgements since it emphasised the important parts of the X-ray pictures used to make the predictions. In medical applications, this transparency is vital as it reveals the model's decision-making process. The model was assessed after training using many criteria: The integration of Grad-CAM with SqueezeNet offers a robust method for automated tuberculosis detection, which might find use in medical diagnostics.

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