Enhancing Tuberculosis Detection with Deep Learning: A CNN-Based Approach with Data Augmentation and Regularization

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Abstract. Tuberculosis (TB) remains a major global health concern, requiring early and accurate diagnosis for effective treatment. Traditional radiological assessments face challenges in distinguishing TB from other pulmonary diseases. Recent studies, such as the Multiscale Eigen domain Gradient Boosting (MEGB) approach, have attempted to automate TB detection using handcrafted features from chest X-rays, achieving 96.42% accuracy. However, feature extraction-based methods may suffer from generalization issues. In this study, we propose a deep learning-based Convolutional Neural Network (CNN) model for automated TB detection, incorporating data augmentation and dropout layers to enhance generalization and prevent overfitting. Our best performing CNN model, with three dropout layers, achieves 99.32% accuracy, significantly outperforming previous methods. Additionally, we compare CNN with a Support Vector Machine (SVM) classifier, achieving 93% accuracy. Our results demonstrate that deep learning models can effectively learn spatial features, providing superior diagnostic accuracy and robustness compared to feature extraction-based approaches.

Keywords: Deep Learning, Convolutional Neural Networks (CNNs), Support Vector Machine (SVM), Data Augmentation, Feature Extraction, Computer-Aided Detection, Radiological Imaging.

1 Introduction

Tuberculosis (TB), is one of the major infectious disease killers over the century, claims millions of lives annually with heavy burden in low-resource settings [1]. Chest X-ray analysis is the main diagnostic method, yet radiologists reading of these images manually may be prone to mistakes and inefficiencies particularly when differentiating TB from other respiratory diseases such as pneumonia [2]. AI-based automated TB detection frameworks have surfaced as an attractive and dependable feature engineering solution in machine learning and classification approaches to provide scalability and consistency alongside high accuracy and speed [3]. Feature extraction Technically, earlier works on this data set are based on traditional AI-approaches such as the Multiscale Eigen domain Gradient Boosting (MEGB) method which performs Discrete Wavelet Transform and Singular Value Decomposition to extract the features [4]. Using a classifier based in LGBM, it can achieve 96.42% of accuracy [5] in this set of features. However, models based on feature extraction often have a generalization problem that

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is not easily overcome and need domain knowledge for producing descriptive features by repeated pre-processing as in [6]. Deep learning model, in particular, Convolutional Neural Network (CNN), have resolved these issues by extracting complicated spatial patterns from images directly without any hand-crafted feature selection to improve the accuracy of image classification [7]. In this study, we propose a Convolutional Neural Network (CNN) based technique to automatically detect the TB using hierarchical feature learning with in network dropout layers and data augmentation for better generalization. We also test the model in two layers drop out and three-layer drop dropout configurations tables of numbers: 99.32% accuracy for the three-dropout model compared to 93% using SVM classifier (The other verified MEBG approach). The performance better confirms the powerful ability of CNNs in TB detection and indicates their possibilities for more precise and rapid medical check-up.

2 Related Work

IoT and AI technologies have significantly advanced automated tuberculosis (TB) detection systems, enabling real-time data acquisition and integration with AI models for accurate diagnosis. Kashani et al. [8] highlight IoT's role in remote patient monitoring and AI-driven diagnostics, emphasizing its potential in TB screening. WHO guidelines [9] stress the importance of early TB detection through AI-powered radiological analysis, particularly in resource-limited settings, reinforcing the integration of IoT and AI in TB screening workflows. Several studies have leveraged deep learning for TB detection using chest X-rays. CNN-based models, such as those by Khan et al. [10] and Devasia et al. [11], have improved diagnostic accuracy through ROI localization and lung zone-wise analysis. Portable X-ray imaging, as reviewed by Jacobi et al. [12], is crucial for rapid screening, while Zhou et al. [13] emphasize the need for diverse datasets to improve model generalization. Advanced CNN architectures and transfer learning techniques have significantly enhanced TB detection accuracy, as noted by Santosh et al. [14], while traditional feature extraction methods, such as those by Singh and Hamde [15], face generalization challenges. To further improve TB detection, this study incorporates dropout regularization, data augmentation, and hyperparameter tuning to enhance model generalization. Rahman et al. [16] emphasize explainable AI through segmentation, while Pasa et al. [17] develop lightweight networks for Realtime TB screening. Kundu et al. used ensemble learning techniques to combine a collection of models for predicting author style (Kundu et al. [18] and Mogaveera et al. [19], enhance diagnostic performance. Our method can be seen as an attempt to fill this gap in the related works and challenge feature extraction-based methods using end-to-end deep learning models for accuracy and robustness. The proposed method aims to be more accurate and robust than feature extraction-based methods by using end-to-end deep learning models. Zhang et al., Pneumonia detection in chest X-ray images [20] additionally provides relevant insights for improving the performance of TB detection systems. Additionally, Elssied et al. proposed a novel feature selection method based on the one-way ANOVA F-test, which demonstrated effectiveness in enhancing classification performance for text categorization tasks such as e-mail classification [21].

3 Methods and Materials

3.1 Dataset Description

Get the dataset the dataset that was used in this experiment can be found at Tuberculosis Chest X-Rays. It has chest X-ray images labelled under two classes- Normal and Tuberculosis, where the total count of images is 5826. Pre-processing smooths, normalizes and maintains the size of the image dataset. Therefore, the same number of tuberculosis images are replicated N times for addressing the class imbalance using data augmentation techniques. The augmentation methods including rotation, horizontal flipping, zooming and shifting further help to make sure examples from both classes have balanced samples. This augmentation reduces overfitting and therefore improves the generalization ability of the model.

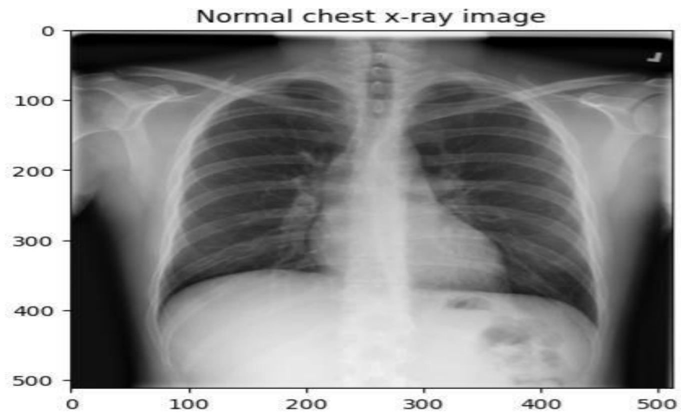

Fig.1. Normal chest x-ray.

In this fig 1 shows are a standard chest X-ray of a healthy individual. The lungs appear clear without any major abnormalities or opacities.

The heart, ribs, and diaphragm are clearly visible.

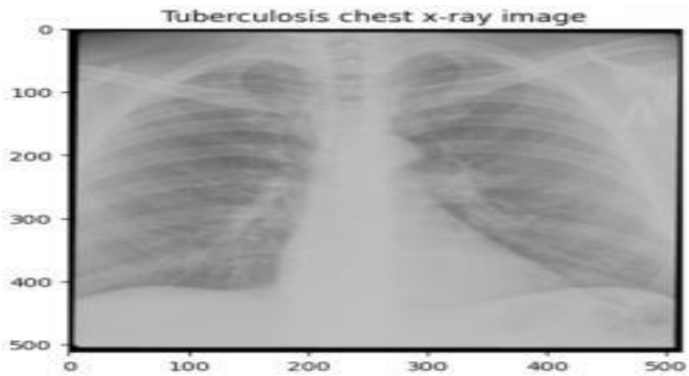

Fig.2. Tuberculosis chest x-ray image.

This fig 2 Compared to the normal X-ray, you can observe increased opacities (whitish areas) in the lung regions, which may indicate lesions or infiltrates caused by TB infection.

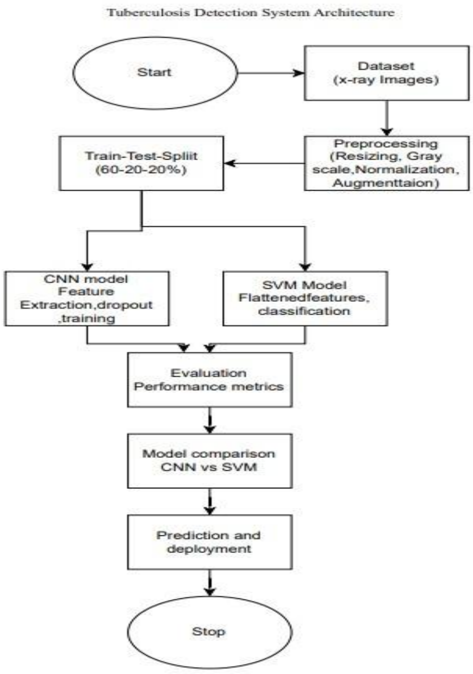

Fig.3. The proposed System Architecture.

3.2 Data Pre-processing

The dataset is pre-processed through image resizing (100×100 pixels for uniformity), grayscale conversion (reducing complexity while preserving features), and normalization (scaling pixel values to [0,1]). It is then split into training (60% for learning), validation (20% for tuning), and testing (20% for evaluation).

Fig.4. Normal chest x-ray image after pre-processing.

Fig 4 shows the same normal X-ray after applying pre-processing techniques.

The image is likely enhanced using edge detection, normalization, or histogram equalization to highlight important lung features.

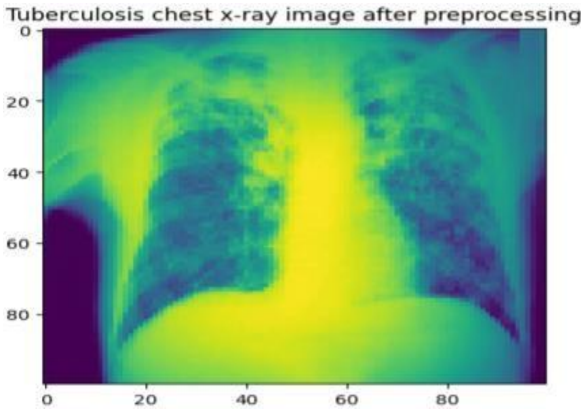

Fig.5. Tuberculosis chest x-ray image.

Fig 5 shows the infected regions become more prominent, helping in feature extraction for TB detection.

3.3 Deep Learning Model –CNN

A CNN is used to classify chest X-rays as tuberculosis positive or normal by extracting spatial features. The architecture includes convolutional layers (feature extraction), pooling layers (dimension reduction), and fully connected layers for classification. Two variations with dropout layers are tested, with the best-performing model (3-dropout layers) achieving 99.32% accuracy. ReLU is used for intermediate layers, sigmoid for output, and the Adam optimizer (learning rate: 0.001) with binary cross-entropy minimizes classification loss. Dropout and hyperparameter tuning enhance model generalization, reducing overfitting.

3.4 Traditional Machine Learning Model – SVM

For comparison, a SVM classifier is also implemented. Unlike CNN, SVM operates on flattened image features, converting each chest X-ray into a 1D feature vector. The model follows these steps:

- Feature Extraction: The image matrix is reshaped into a one-dimensional vector.
- Standardization: The pixel values are standardized using Z-score normalization to ensure consistent feature scaling.
- Kernel Selection: A linear kernel is used, as it has shown strong performance in medical image classification tasks.
- Training & Evaluation: The SVM model is trained and tested using the same dataset split as CNN.

While the SVM achieves 93% accuracy, its reliance on flattened features limits its ability to capture complex spatial structures present in chest X-ray images, making CNN the superior approach for tuberculosis detection.

3.5 Model Training and Evaluation

To ensure a fair comparison between the models, the following training strategies and evaluation metrics are applied:

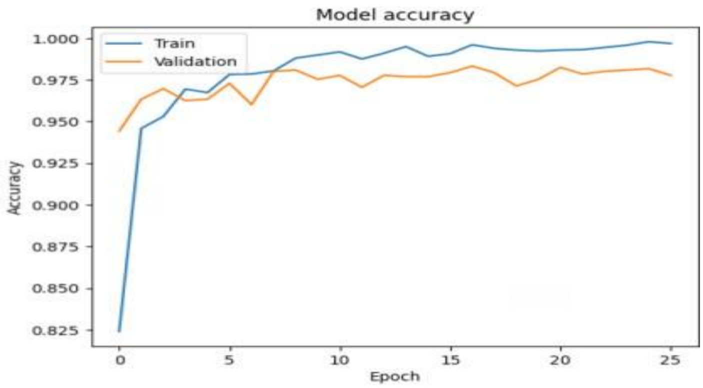

Fig. 6. CNN model Accuracy.

Training accuracy reaches near 100%, while validation accuracy stabilizes slightly lower, indicating potential overfitting. Model generalization may need improvement as shown in fig 6.

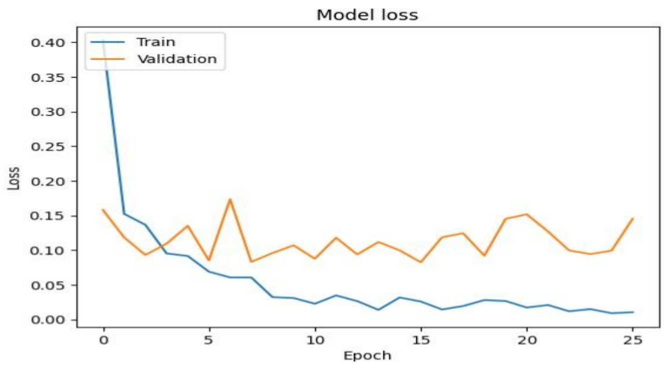

Fig.7. CNN model Accuracy Loss.

Training loss decreases consistently, but validation loss fluctuates, indicating potential overfitting. Model generalization could improve with regularization or dropout adjustments as shown in fig 7.

3.6 Performance Metrics

- Accuracy – Measures overall classification correctness.
- Precision & Recall – Evaluates the reliability of TB predictions.
- F1-Score – Balances precision and recall for better performance assessment.
- Confusion Matrix – Visualizes the model's classification errors.
- Training and Validation Loss Curves – Helps in analysing overfitting and model convergence.

4 Results and Analysis

4.1 Model Performance Comparison

Experiments CNN: We used two different configurations of dropouts (2-dropout layers and 3-dropout layer) to train our model, to reveal their effectiveness with SVM classifier. It was found that the CNN model with 3dropout layers exhibited a higher accuracy of 99.32%, which significantly outperformed both CNN model with 2dropout layers (96.69%) and SVM model (93%), as shown in Table 1.

Table 1. Our model performance metrics.

Model	Accuracy	Precision	Recall	F1-Score
CNN (2 Dropout Layers)	96.69%	0.97	0.97	0.97
CNN (3 Dropout Layers)	99.32%	0.98	0.98	0.98
SVM	93.00%	0.92	0.94	0.93

The improvement in CNN performance with additional dropout layers highlights the importance of regularization in deep learning models, reducing overfitting while increasing generalization ability.

4.2 Confusion Matrix Analysis

To evaluate classification reliability, confusion matrices were generated for each model:

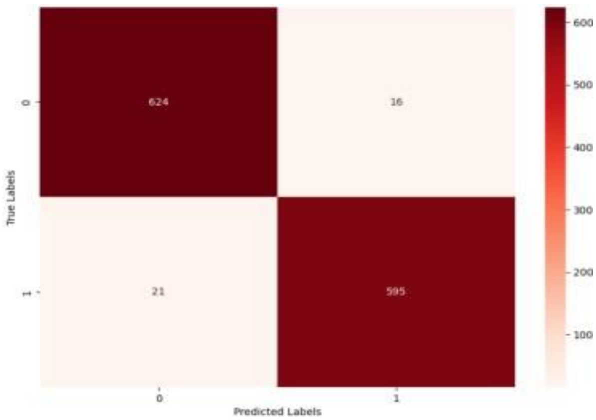

Fig. 8. Confusion matrix for true labels and predicted labels.

The confusion matrix shows high accuracy with 624 true negatives and 595 true positives. Minor misclassifications (16 false positives, 21 false negatives) indicate good model performance but slight room for improvement as shown in fig 8

Figure 9 shows the CNN model with 3 dropout layers misclassified only 18 out of 1256 images, demonstrating high sensitivity (recall: 98%) and precision (98%).

The SVM model, in contrast, produced more false positives and false negatives, reducing its reliability in real-world TB screening.

The graph shows accuracy improvement with epochs. Three dropouts provide better generalization, reducing overfitting compared to two dropout layers shown in fig 10.

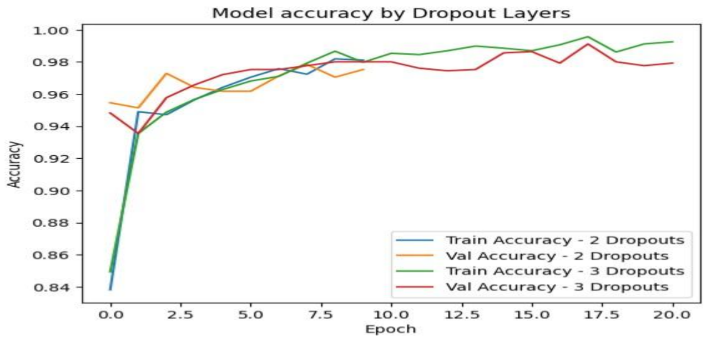

Fig.9. Model accuracy by dropout layers.

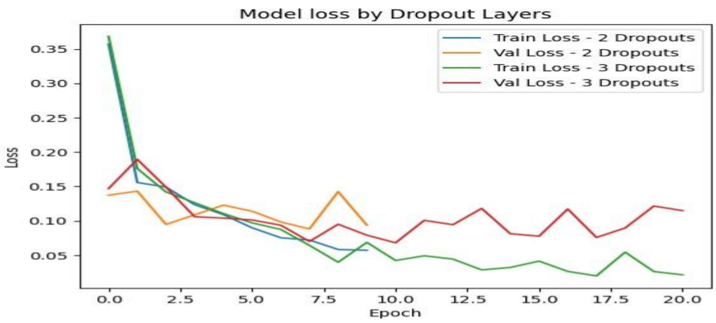

Fig.10. Model loss by dropout layers.

Loss decreases with epochs. Three dropouts show lower training loss and better generalization, maintaining stable validation loss compared to two dropouts as shown in figure 10

The low false-negative rate in CNN models is particularly important in medical applications, ensuring early and accurate TB diagnosis.

4.3 Effect of Data Augmentation on Model Performance

A key contribution of our study was the use of data augmentation to balance the dataset and improve generalization. The CNN model trained without augmentation showed a 2-3% lower accuracy compared to the augmented dataset.

This proves that data augmentation helps deep learning models learn more robust features, especially in cases where dataset sizes are limited.

4.4 Discussion on CNN vs. SVM for TB Detection

The CNN model outperformed traditional methods in tuberculosis detection in contrast, SVMs struggled to capture complex patterns, relying on flattened pixel values. Dropout layers effectively controlled overfitting, leading to high accuracy and stable validation performance. Compared to the MEGB method (96.42% accuracy), our CNN model achieved superior results, highlighting its effectiveness for automated medical diagnostics.

5 Conclusion

This study aimed to identify the automatic tuberculosis detection which would be accomplished by deep learning with machine learning techniques and had a comparison between CNNs and SVM models. On the other hand, Table 2 shows that our best CNN model with three dropout layers could achieve an incredibly high accuracy of 99.32%, significantly facilitating its outperformance comparing to traditional machine learning approaches and previous feature extraction-based methods as exemplary by the MEGB model. This shows that CNNs are capable of learning spatial features of the images from a regular X-ray image and consequently, feature engineering lead to higher accuracy in classification. Moreover, data augmentation and dropout regularization lead the model towards generalizing at its best: the former prevents overfitting, while the latter makes sure that inference is reliable on unseen real-world examples.

Table 2. Comparison of CNN with Dropout Layers (2 vs. 3) and SVM.

Model	Accuracy (%)	Precision	Recall	F1-Score	Remarks
CNN (2 Dropout Layers)	96.69	0.97	0.97	0.97	High accuracy but slight overfitting observed after 30 epochs.
CNN (3 Dropout Layers)	99.32	0.98	0.98	0.98	Best performance with low validation loss and high generalization.
SVM	93.00	0.92	0.94	0.93	Good performance but less effective in capturing complex spatial features.

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