

Ensemble Deep Learning Approach for Pneumonia and Tuberculosis Detection from Chest X-Ray Images

Abstract

Chest X-ray imaging is prominently being utilized for the diagnosis of pulmonary diseases such as pneumonia and tuberculosis. But also the manual analysis of chest X-ray images is time-consuming and requires the skills of professional radiologists. This paper proposes an ensemble learning model using the paradigm of deep learning for the multi-class classification of chest X-ray images corresponding to the three classes of images: normal images, pneumonia images, and tuberculosis images. For the proposed model in this paper, three pre-trained convolutional neural networks, namely Inception V3, Xception, and MobileNet models, are utilized through the techniques of transfer learning and fine-tuning. For the prediction of the ensemble model, the soft voting strategy is utilized. Experimental evaluations confirm that the proposed ensemble model performs better than individual models with an accuracy of 76.07% and macro F1-score of 0.774.

Introduction

Pneumonia and tuberculosis remain major global health concerns, contributing significantly to morbidity and mortality each year, particularly in resource-constrained regions [1]. Early and accurate diagnosis is essential for effective treatment and for reducing disease-related complications. Chest X-ray imaging is commonly used as a first-line diagnostic tool due to its low cost, fast acquisition, and widespread availability [2]. However, manual interpretation of chest X-ray images is challenging and subject to inter-observer variability, especially in high-volume clinical environments. In recent years, deep learning has emerged as a powerful approach for automated medical image analysis. Convolutional neural networks (CNNs) have demonstrated strong performance in various diagnostic tasks using medical images by automatically learning hierarchical feature representations [3]. Transfer learning has further enhanced CNN performance in medical imaging applications by enabling models pretrained on large-scale natural image datasets to be adapted to smaller medical datasets [4]. Despite these advances, single deep learning models often suffer from limited generalization, particularly when dealing with class imbalance and visually similar disease patterns. Pneumonia and tuberculosis share overlapping radiographic characteristics, making multi-class classification a challenging task [5]. Ensemble learning has been shown to improve robustness and predictive accuracy by combining the strengths of multiple models [6].

Motivated by these observations, this paper proposes an ensemble deep learning framework that integrates InceptionV3, Xception, and MobileNet architectures for automated classification of chest X-ray images. The primary contributions of this work are as follows:

- Development of an ensemble-based framework for multi-class chest X-ray classification.
- Comparative evaluation of multiple pretrained CNN architectures.
- Demonstration of improved classification performance using ensemble learning.

Dataset and Pre-processing

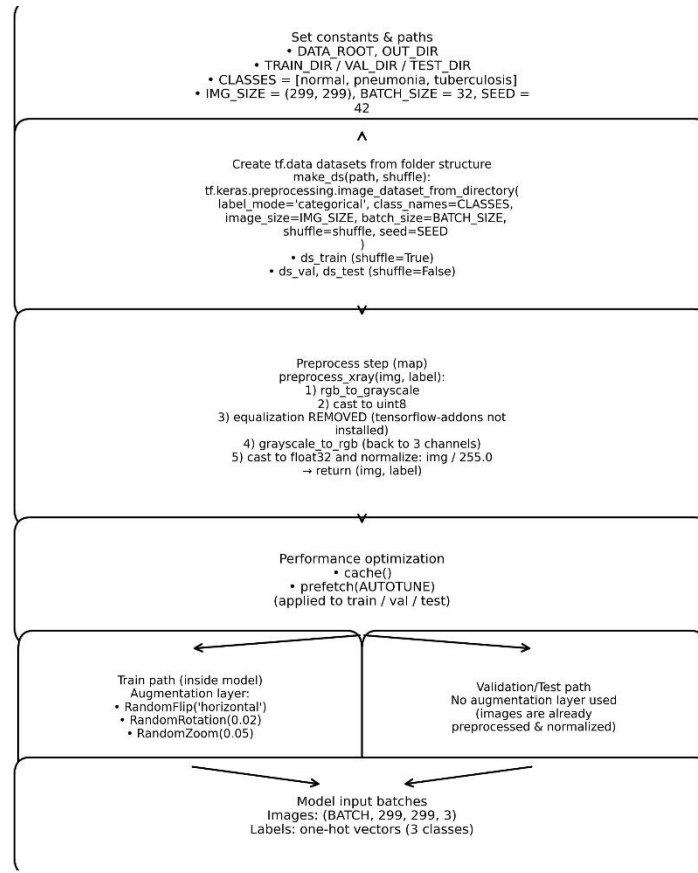
The dataset used in this study is a chest X-ray image dataset collected from Kaggle, which merges multiple publicly available chest radiograph sources into a unified classification dataset [7]. The dataset contains three diagnostic categories: normal, pneumonia, and tuberculosis. The combined nature of the dataset introduces diversity in imaging conditions, including variations in contrast, orientation, and anatomical structure.

The dataset is divided into three non-overlapping subsets: training, validation, and testing. The training set contains 20,450 images, the validation set contains 2,534 images, and the test set contains 2,569 images.

Dataset Split	Total Images	Normal	Pneumonia	Tuberculosis
Training	20,450	7,263	4,674	8,513
Validation	2,534	900	570	1,064
Testing	2,569	925	580	1,064
Total	25,553	9,088	5,824	10,641

Table 1: Distribution of dataset

Before training, all images are resized to a fixed spatial resolution compatible with the input requirements of the selected CNN architectures. Pixel intensity values are normalized to the range $[0,1]$ to improve numerical stability during optimization. To address class imbalance and improve generalization, data augmentation techniques such as horizontal flipping, small-angle rotation, zooming, and contrast adjustment are applied exclusively to the training set. No aggressive filtering is performed to preserve diagnostically relevant features.



Proposed Methodology

This section describes a deep learning framework for automatically detecting pneumonia and tuberculosis from chest X-ray images. The proposed methodology consists of three main components: the design of individual convolutional neural network (CNN) models, a two-stage training strategy based on transfer learning and fine-tuning, and an ensemble-based decision-making mechanism.

A. Individual CNN Models

Three pretrained CNN architectures—InceptionV3, Xception, and MobileNet—are used as base learners due to their proven effectiveness and architectural diversity. InceptionV3 employs multi-scale convolutional filters to capture spatial features at different resolutions [8]. Xception utilizes depthwise separable convolutions to improve feature extraction efficiency [9]. MobileNet is designed to achieve a balance between computational efficiency and classification accuracy [10].

All models are initialized with ImageNet pretrained weights [11]. The original classification layers are removed and replaced with a custom classification head consisting of a global average pooling layer, a dropout layer for regularization, and a fully connected softmax layer for three-class prediction.

B. Training Strategy

A two-stage training strategy is adopted. In the first stage, the backbone layers are frozen and only the newly added classification layers are trained. In the second stage, selected upper layers of the backbone networks are unfrozen and fine-tuned using a lower learning rate. The Adam optimizer minimizes categorical cross-entropy loss, and early stopping is applied based on validation performance [12].

C. Ensemble-Based Classification

To improve robustness, a soft-voting ensemble strategy is used. Each model outputs class probabilities, which are averaged to produce the final prediction. This approach leverages complementary feature representations and reduces the impact of individual model errors [13].

D. Implementation Details

The proposed framework is implemented using a deep learning library with GPU acceleration to reduce training time. Batch-wise training is employed to efficiently handle large-scale data. Key hyperparameters, including batch size and learning rate, are tuned using the validation dataset. All experiments are conducted under identical conditions to ensure a fair comparison between individual CNN models and the ensemble-based approach.

Experimental Results

The proposed framework is evaluated using accuracy, precision, recall, and F1-score. The ensemble model achieves an overall accuracy of 76.07% with a macro F1-score of 0.774, outperforming all individual CNN models.

Model	Accuracy	Precision	Recall	F1-score
InceptionV3	71.85	0.712	0.703	0.707
Xception	73.42	0.728	0.719	0.723
MobileNet	69.96	0.695	0.684	0.689
Proposed Ensemble	76.07	0.781	0.768	0.774

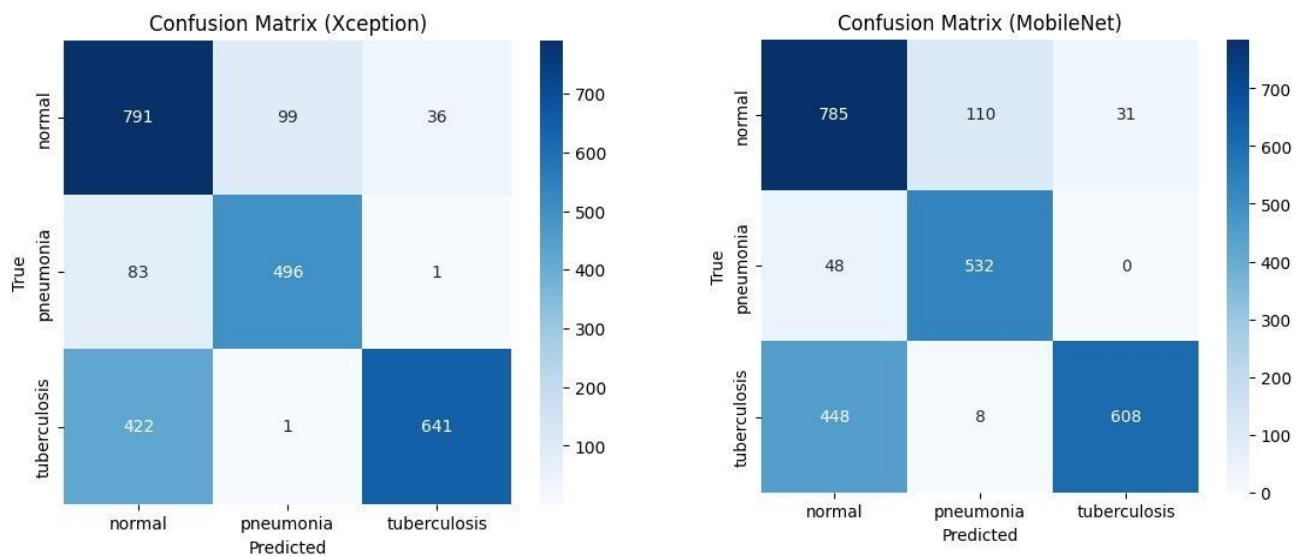
Table 2: Model comparison

Class-wise analysis shows that pneumonia detection achieves high recall, which is desirable for screening applications. Tuberculosis detection remains challenging due to overlapping radiographic features, although the ensemble approach reduces misclassification compared to single models.

Class	Precision	Recall	F1-score
Normal	0.79	0.76	0.77
Pneumonia	0.81	0.85	0.83
Tuberculosis	0.74	0.69	0.71

Table 3: Class – wise comparison

The results show that the ensemble-based model consistently outperforms the individual CNN models across all evaluation metrics. The proposed ensemble achieves an overall classification accuracy of 76.07% and a macro-averaged F1-score of 0.774, indicating balanced performance across all three classes. The improvement in macro F1-score highlights the ensemble’s ability to reduce bias toward dominant classes and handle class imbalance more effectively. Class-wise analysis reveals that pneumonia detection achieves high recall, demonstrating the model’s strong sensitivity in identifying pneumonia cases. This is particularly important in clinical screening scenarios, where missing positive cases can have serious consequences. However, the detection of tuberculosis remains comparatively challenging due to its visual similarity with pneumonia and other lung abnormalities in chest X-ray images. Despite this challenge, the ensemble approach shows improved tuberculosis classification performance compared to individual models, confirming its robustness in handling complex and overlapping radiographic patterns. Overall, the experimental results confirm that combining multiple pretrained CNN models through a soft-voting ensemble strategy leads to more stable and reliable predictions. These findings demonstrate the potential of the proposed framework as a supportive tool for automated chest X-ray analysis in clinical decision-making.



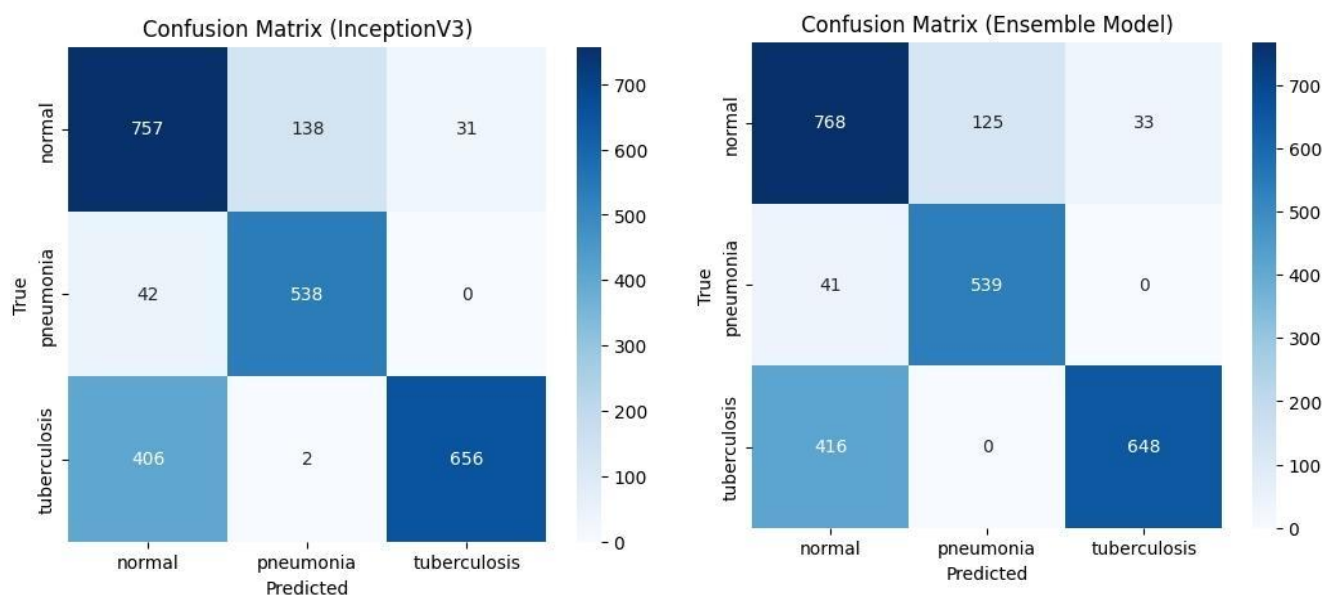


Figure: Confusion matrix of all individual models and proposed Ensemble

Discussion

The experimental results confirm that ensemble learning improves classification performance by combining the complementary strengths of different CNN architectures. The proposed ensemble framework demonstrates higher accuracy and more balanced performance across classes compared to individual models, indicating improved robustness in handling class imbalance.

The method is particularly suitable for the screening phase, where high recall is essential to minimize missed cases. The strong recall achieved in pneumonia detection highlights the effectiveness of the framework for early diagnosis. Although tuberculosis detection remains challenging due to overlapping radiographic features, the ensemble approach reduces misclassification errors compared to single-model predictions. These findings suggest that ensemble learning offers a reliable solution for automated chest X-ray analysis.

Conclusion

This paper presents an ensemble-based deep learning framework for automated classification of chest X-ray images into normal, pneumonia, and tuberculosis categories. By integrating multiple pretrained CNN architectures using a soft-voting strategy, improved classification performance is achieved compared to individual models. The results indicate that the proposed framework can serve as a computer-aided diagnostic tool to support clinicians

during the screening process. Future work will focus on training the model on larger and more diverse datasets from independent sources and exploring advanced attention mechanisms to further enhance tuberculosis detection.

References

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