Machine Learning-Based Classification System for Tuberculosis Detection Using Locally Collected Radiographs

Imran kamal Mirza[1], Muhammad Rehman[1], Adeel Ahmed[1], Fawad Nasim[1] and Sohail Masood Bhatti[1]

Received: 17 April,2024; Accepted: 20 Jun, 2024; Published: 1 Oct, 2024

Abstract: Tuberculosis (TB) is still a severe public health problem. Pakistan also has a high burden of TB and is ranked 6th among in top 30 countries nationwide. There are many computer-aided detection (CAD) systems that can detect TB. But the problem is that all the available systems are developed and tested within developed states and when they are tested for middle-income countries their performance varies. The main purpose of this study is to develop a machine learning-based classification system for Tuberculosis detection using locally collected radiographs which is specifically designed for the middle-income countries according to their socio-economic factors. In this study, we first collect a dataset comprising of X-ray images, The Digital Imaging and Communications in Medicine (DICOM) file format. These X-ray images were collected from the Provincial TB Control Program in Punjab, which had conducted Chest camps using mobile X-ray vans in remote areas across various districts within the Punjab Province. We apply data augmentation and a convolutional neural network (CNN) from the beginning. that the term "Conv" shows the convolution layer with the 380 TB positive and 421 Normal X-rays. In training accuracy 99.53%, validation accuracy 100%, Test accuracy 99.17%, Test loss 0.0844.

Keywords: Augmentation, CAD, CNN, Detection, Tuberculosis, Radiographs

1- Introduction

As per the World Health Organization's (WHO) Global Tuberculosis Report 2023 **[1]** the worldwide situation of tuberculosis (TB) is still a severe public health problem. Pakistan also has a high burden of tuberculosis (TB) and is ranked 6th among the top 30 countries with the highest TB burden nationwide. In 2023, an estimated 467,000 individuals were diagnosed with TB in Pakistan, and 66,000 people died.

[1]*Faculty of Computer Science and Information Technology, The Superior University, Lahore, 54600, Pakistan*

[*]*Corresponding Author imrankamal.ptp@gmail.com*

The report claims that Pakistan has made some progress in decreasing the TB load. However, extra struggles remain required to achieve the overall TB aims set by the WHO. The country has shown a large decline in TB incidence (Fig. 1) [1] and deaths (Fig. 2) but, the speed of overcome is not enough to achieve the WHO targets [1]. The country's TB response is facing challenges in finding and treating patients and in providing quality care. The WHO suggests that Pakistan must rise in its struggles to reach and treat TB cases, specifically in the middle of vulnerable residents, improve the quality of TB care, and also invest in studies, and increase the number of new TB diagnoses and treatment facilities. Here are multiple computer-aided diagnostics (CAD) systems and artificial intelligence (AI) tools that are specifically designed and tested for TB detection, mainly in the field of chest radiography. These CAD systems use machine learning algorithms

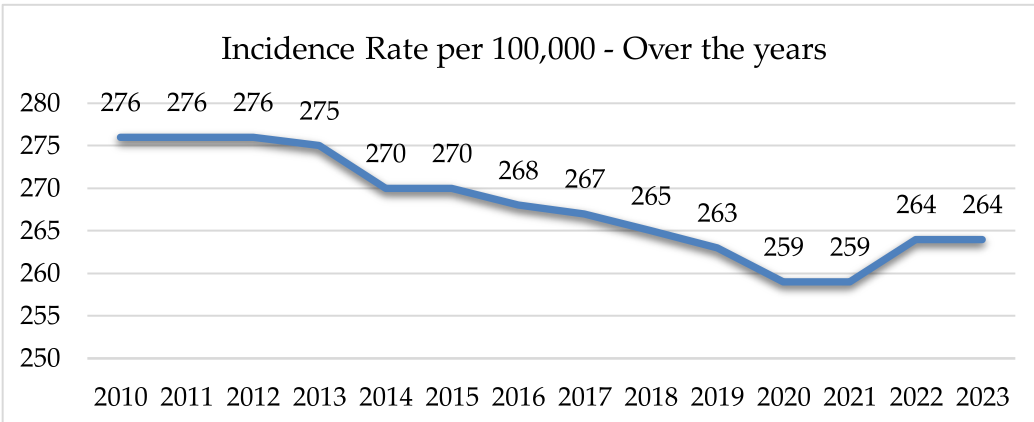


Figure 1. TB incidence rate per 100,000 people in Punjab, Pakistan

evaluate X-rays of the chest and look for indications of tuberculosis. A CAD system named "LungCARE," created by scientists at the University of California, San Francisco, is one instance; it has been utilized in several investigations utilizing images from chest radiographs of American patients. A deep learning system known as "TB ResNet," created and developed by Massachusetts General Hospital, was employed in other investigations on chest X-ray pictures obtained from patients in South Africa and India. Finding and treating patients as well as delivering high-quality treatment are obstacles facing the nation's TB response. According to the WHO, Pakistan has to step up efforts to identify and treat TB patients, particularly those that are amid vulnerable populations, and enhance the standard of TB care as well as fund research and build more new facilities for the detection and treatment of tuberculosis. Various artificial intelligence (AI) tools and computer-aided diagnostics (CAD) systems have been specially developed and tested for tuberculosis (TB) diagnosis, primarily in the field of chest radiography. These CAD systems analyze chest X-rays and look for indications of tuberculosis using machine learning methods. One such is a computer-aided diagnosis (CAD) system named "LungCARE," created by scientists at the University of California, San Francisco. It has been utilized in several investigations using images from chest radiographs of US patients. The Massachusetts General Hospital created and developed a deep learning system known as "TB ResNet," which was also utilized for chest X-ray pictures from patients to identify the actual presumed instances of tuberculosis, this study intends to apply a machine learning-based classification method for tuberculosis identification utilizing locally obtained radiographs. Due to varying socioeconomic conditions, the current technologies available to identify tuberculosis germs were developed and tested in the United States, India, and South Africa, and may not be particularly effective in determining the exact frequency of tuberculosis in Pakistan. Previous research has demonstrated that machine learning algorithms created in affluent nations do not perform as well in middle-income nations.

For example, a different study found that a machine-learning model developed in India and tested in South Africa performed worse than the model tested in India for TB identification. According to the study, differences in imaging technology, patient characteristics, and radiological techniques may have had an impact on the model. A deep learning system for TB diagnosis that was created and tested in China performed worse when tested in India, according to different research.

The research discovered that socioeconomic considerations could have had an impact on the model. In light of these findings, it's critical to modify or create new technologies that are tailored to the environment and people of Lahore, Pakistan, to improve the accuracy of tuberculosis detection. To fill this vacuum in the literature, this project will create a machine learning-based categorization system for

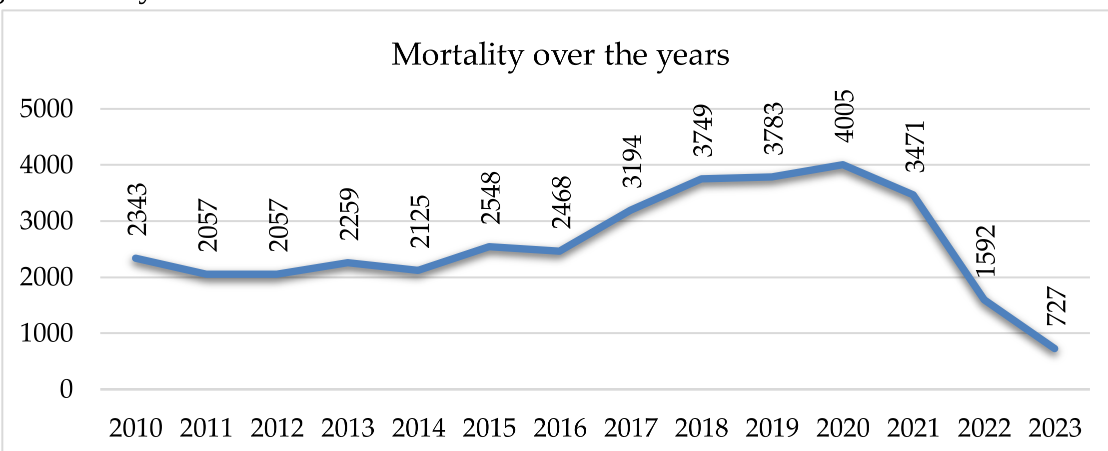


Figure 2. TB Deaths over the years in Punjab, Pakistan

tuberculosis detection using locally obtained radiographs tailored to the Lahore, Pakistan, environment, thereby offering a more precise and dependable TB detection technique. The absence of a tuberculosis detection method tailored to the environment and population of Punjab, Pakistan, is a gap in this study. Artificial intelligence (AI) and computer-aided diagnostics (CAD) systems are available for the detection of tuberculosis (TB); however, they were developed and tested in other nations, such as China and the United States, and may not be representative of the environment and patient population in Punjab, Pakistan. Recent research has demonstrated that because of differences in patient characteristics, radiological techniques, and other factors, deep learning algorithms created in high-income countries do not perform as well in low- and middle-income countries as well as imaging apparatus. Therefore, to give a more precise and trustworthy tool for tuberculosis diagnosis in the region, the CAD-4 system needs to be redesigned for the context of Lahore, Pakistan. This research aims to enhance the identification of genuine tuberculosis cases in Pakistan, a nation with a significant tuberculosis burden, and to support the international endeavor to terminate the tuberculosis pandemic by 2035, as stipulated by the World Health Organization [1].

2- Importance of medical imaging:

Medical images refer to pictures of visual information obtained from several radiology procedures including; radiographs, computed tomography (CT), magnetic resonance imaging (MRI), and ultrasound. Such images are applied for diagnosis, planning further therapy, and, at times, evaluating the disease progression. The questionnaire provides useful information concerning the presumed internal construction and function of the body, which cannot be easily gathered through clinical examination. It describes openly and frequently applied radiology techniques that give images of the human body's internal structure through the transient rays passing through the human frame and capturing the follow-on images on the film. Another widely used imaging is computed tomography or simply CT which helps obtain highly detailed cross-sectional images of the human body using multiple X-ray images taken at different angles. Another imaging is Magnetic Resonance Imaging commonly referred to as MRI, which generates very clear images of the interiors of the body including the organs using radio waves and magnetic fields. Various diseases like Tuberculosis, tumors, cardiac disease, nerve disorders, and all the other diseases can be detected with the help of medical images to treat them hence contributing to finding new therapies for medical research in advancement. There are many other image features as follows:

Texture features such as Haralick features, Local Binary Patterns (LBP), and Gabor filters have been widely used in medical imaging for tasks such as tissue classification, lesion segmentation, and diagnosis. These features have been applied in several studies to accurately differentiate between benign and malignant tumors in mammogram, CT, and MRI images. By combining these texture features with other image features such as shape and size, classification accuracy has been improved compared to using each feature individually.

Unsupervised learning techniques including clustering, dimensionality reduction, autoencoders, anomaly detection, and Generative Adversarial Networks (GANs) can identify forms and irregularities in the images to determine the incidence of various medical diseases in the context of chest X-rays. Anomaly detection algorithms, on the other hand, may recognize images that differ from the norm, whereas clustering algorithms, for instance, can group comparable chest X-ray images based on characteristics like intensity, texture, and form. Principal Component Analysis (PCA) and dimensionality reduction also reduce the number of features in the chest X-ray pictures, which facilitates the algorithm's ability to find patterns and relationships in the data. GANs and auto-encoders can be used to create fresh chest X-ray images that are similar to the original and to represent the image's features in the training dataset, respectively.

3- Literature Review:

Ahmad J, Akram S, Jaffar A et al. reported that the CAD system had a 99% success rate in identifying and categorizing disorders, with an accuracy of 98.5% in detection and 99.16% in classification[2]. Using deep learning (DL), we compare numerous research studies on the diagnosis of tuberculosis using radiography. To identify tuberculosis from chest radiographs, the first study included image preprocessing, data augmentation, X-ray image segmentation, Bharati et al., 2020 [4], and deep learning classification [5]. Two types of U-net are employed for segmenting the X-ray picture, and nine different pre-trained CNNs were applied to determine the real TB presumption. The evaluation's findings include the specificity rate, F1-score, accuracy rate in percentage, precision in percentage, and sensitivity in percentage ChexNet Jeyashree et al., 2022

[3]. The study showed that targeting the chest area of the radiograph through classification and training can increase presumptive findings. The second study performed a separate presumptive meta-data inquiry to evaluate the analytical precision of the chest radiograph (CXR) examined through commercially accessible deep learning-based CAD systems for finding TB. The study used multiple methods to find beginning scores for approximating specificity and sensitivity (Showkatian et al., 2022 [4]. The paper concludes that both studies contribute to improving the accuracy of TB detection through radiographs using deep learning algorithms. S Mumtaz et al. 2024 [5] In the same way that deep learning techniques have shown better accuracy in detecting brain tumors by automatically extracting features and optimizing classification, these approaches can also improve the precision and reliability of tuberculosis detection, leading to more effective treatment outcomes. (Nasim F et al. 2022) [6] Segmentation plays a major role in detecting TB. Conventional machine learning-based approaches have shown remarkable performance in complex problems (Ahmad M, et al. 2022) [7]. However, deep learning approaches outperform them as they provide automatically optimized feature extraction (Nasim F et al. 2023) [8].

There is a lack of proficient CXR readers nationwide for TB findings using CAD software. Tuberculosis detection in rare and limited situations [9], [10], [11], [12]. There are several approaches, fluctuating between the multiple CAD solutions, such as random forests [11] or vectors with shape and texture structures. CAD software is capable of understanding chest radiographs and is commercially available (Qin et al., 2021). With a variety of disadvantages, including the fact that the software is proprietary, closed, and not freely available, deep learning is a component of artificial intelligence (AI), and CAD systems have long been used to support TB screening. Nine distinct Inception-V3 (Szegedy et al., 2015), VGG-19 (Simonyan and Zisserman, 2015), DenseNet-201 (Huang et al., 2022)[11], SqueezeNet (Iandola et al., 2016), and MobileNet-v2 (Sandler et al., 2019) models were tested in recent work by Rahman et al. (2020)[4]. The deep convolutional neural network (CNN) architectures shown here are a few examples. ResNet-18 (He and others, A state-of-the-art deep neural network architecture named ChexNet was utilized to analyze CXR images to find actual tuberculosis (TB) (Rajpurkar et al., 2017).

In a semi-supervised investigation, Kim et al. (2020) [12] employed a deep CNN and confirmed a positive correlation between the algorithm's classification and radiologist interpretations, supporting the notion that deep learning may be applied to accurately label and classify CXRs. When analyzing the screening results, Rajaraman et al. discovered that stacked ensemble networks (SEN) are made up of knowledge-transferred CNNs. Jeyashree K et al. (2022)[5] proposed an approach that uses categorized feature extraction and key characteristics in a two-level hierarchy to classify groups as healthy or sick. Level 2 employs traditional first-order statistical features such as textural features, energy, entropy, contrast, and correlation, whereas Level 1 uses geometrical features that are manually constructed, such as form, size, and perimeter.

These features are extracted from segmented lung fields, and the normality or pathology of a CXR picture is then determined using a supervised classification system. Nevertheless, the computationally costly pre-processing stages necessary for two-level hierarchical decomposition would not function well in a setting with limited resources, much like a CNN ensemble approach a summary of more literature is in the Table. 1.

Table 1 A summary of different CAD and Machine- learning systems

Author/Reference	Name of the Data	Classifier	Accuracy	Sensitivity	Specificity
Hooda et al. [13]	CXR Images (1133)	Ensemble of (AlexNet, GoogleNet & ResNet)	88.24	88.42	88.00
Y. Ban et al. [14]	TBX11K (1078)	CNN	0.90	-	-
Heo et al. [15]	YU, AWH (1000)	Deep-ConvNet ResNet-18	-	-	-
Nguyen et al. [16]	SNUH,BMC, KUHG	AlexNet VGG-16 CapsNet	-	72.00	-
Hwang et al [17]	DEMC,MC,CH (3310)	Alex Net Vgg-16 Vgg-19 Resnet-50 Resnet-101 Resnet-152 Ensemble	84.00	-	-
Limpiyakorn [18]	MC, CH (1007)	Modified Alexanet Modified Vggnet Alexnet Vgg-16 Vgg-19 Xception Resnet-50	94.56	-	-

3.1 Data Collection

In this study, we started by gathering a dataset of radiographs in the DICOM file format. The data was obtained from the Provincial TB control program in Punjab. They conducted chest camps using mobile X-ray vans in remote areas of various districts in the Punjab Province.

3.2 Data preprocessing and augmentation

The current study indicates data amplification techniques were used. Data augmentation has reportedly been shown to increase the classification accuracy of deep learning systems. [19], [20]. Additionally, data augmentation can pointedly raise the samples for training data. Here, we can apply the image rotation, augmentation with range 10 and width modification range for 0.1, and the horizontal shift for 0.1 that shows the models of image augmentation. Later data augmentation, 461 radiographs were fitted for the training. (54% Normal and 46% TB Positive). Visual Comparison of Normal and Tuberculosis-Positive Chest X-Ray Images (Fig. 3).

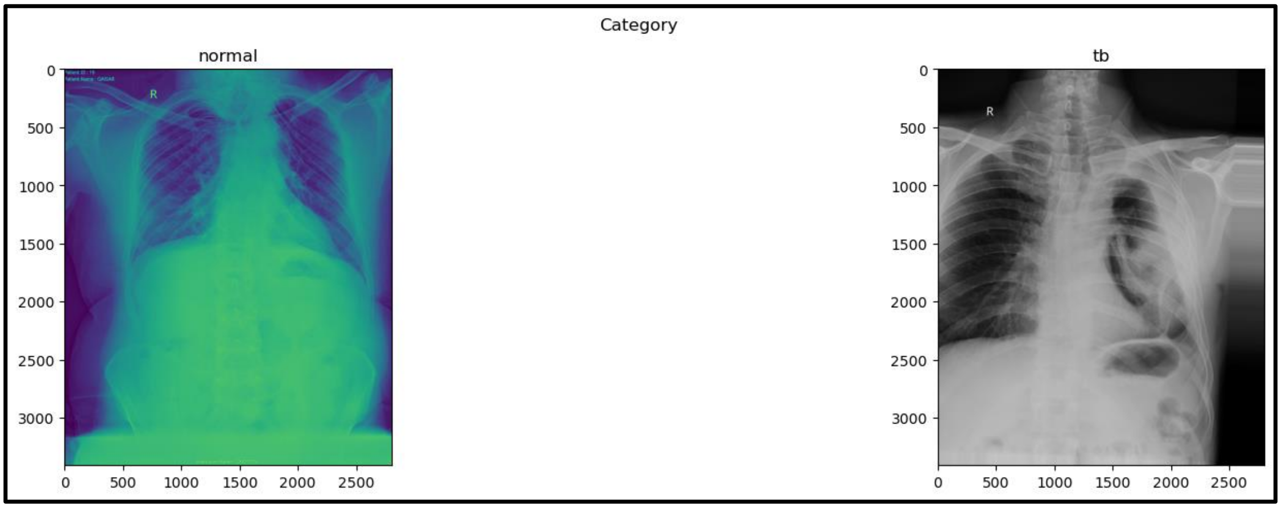
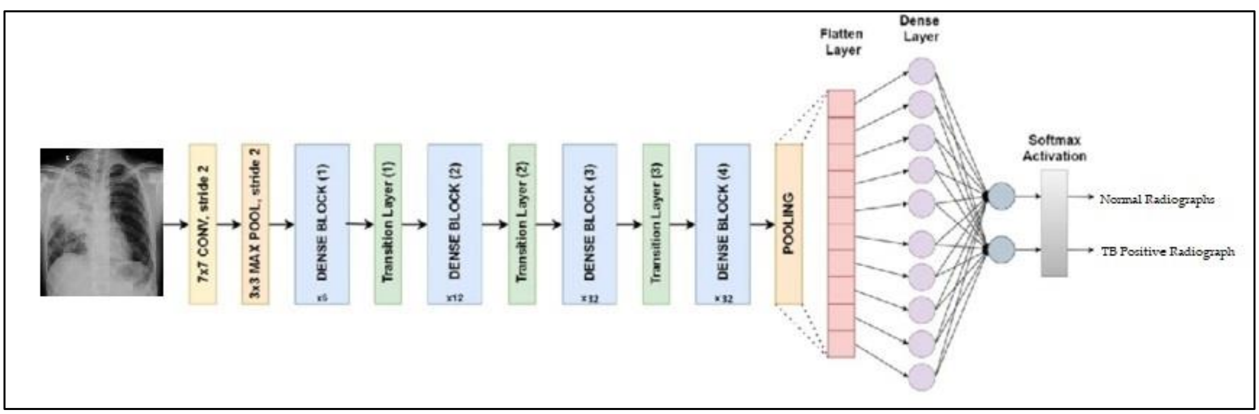


Figure 3 Visual Comparison of Normal and Tuberculosis-Positive Chest X-Ray Images

3.3 DenseNet169

We used DenseNet169 as the base model, a pre-trained deep convolutional neural network known for its remarkable performance across various computer vision tasks. We customize this model by adding our classification layers, including a global average pooling layer to reduce the size of the feature maps, two fully connected dense layers with a ReLU activation function, and a dropout layer to avoid overfitting. The output layer has 2 units with a soft-max activation function to produce class probabilities. We trained this model with the Adam optimizer and categorical cross-entropy loss for 10 epochs, incorporating early stopping and model checkpointing to prevent overfitting—denseNet-



Based Convolutional Neural Network for TB Detection in Chest Radiographs (Fig. 4).

Figure 4 DenseNet-Based Convolutional Neural Network for TB Detection in Chest Radiographs

2.4. Data Augmentation and Results

The Tuberculosis (TB) image dataset underwent a data augmentation process to improve its distribution and increase its efficacy in diagnosis. The data augmentation techniques used included rotation, width and height shift, brightness range, shear, zoom, horizontal flip, and fill mode. The "TBPositive" category's original photos were resized, given a horizontal flip, and then saved as augmented photographs in a special directory. To maintain a balanced class distribution, the number of augmented images produced for every original image was calculated. Following data augmentation, the final distribution produced a balanced dataset including 380 TB-positive photos and 421 normal images. The dataset was partitioned into training, validation, and test sets. The model architecture made use of a pre-trained DenseNet169 model with unique classification layers. To prevent overfitting, the model was trained on the training set for 10 epochs with early stopping and model checkpoints. Neural Network Model Architecture and Parameter Summary (Table. 2).

Table 2. Neural Network Model Architecture and Parameter Summary

Layer (type)	Output Shape	Param #
rescaling_1 (Rescaling)	(None, 224, 224, 3)	0
densenet169 (Functional)	(None, 7, 7, 1664)	1264288 0
flatten_1 (Flatten)	(None, 81536)	0
dense_6 (Dense)	(None, 256)	2087347 2
dropout_1 (Dropout)	(None, 256)	0
dense_7 (Dense)	(None, 2)	514

A neural network model's architecture is shown in a table, which also includes information about the number of trainable parameters in each layer, the order of layers, and their output forms. The model starts with a "Rescaling" layer that adjusts the input data to a standardized range. It has no trainable parameters. Next, a "DenseNet169" layer, a pre-trained convolutional neural network, produces feature maps of size 7x7 with 1,664 channels. It has 12,642,880 trainable parameters. Following that, a "Flatten" layer reshapes the output from DenseNet169 into a single flat vector.

A "Dense" layer reduces the dimensionality of the data to 256 units, introducing 20,873,472 parameters to prevent overfitting, a "Dropout" layer randomly deactivates some units during training. Finally, the model includes another "Dense" layer that reduces the output to 2 units, with 514 parameters.

3. Results

The model achieved high accuracy, with a training accuracy of 99.53% and a validation accuracy of 100%. Following that, the model was assessed using the test set, producing a test loss of 0.0844 and a test accuracy of 99.17%. Additional information about the model's performance was given by the confusion matrix (Fig. 5) and classification report (Table 3), which showed good accuracy for both classes. Training and evaluation accuracy and loss graphs were supplied to visualize the model's learning progress over epochs, and a random selection of images from both categories was shown for visual examination along with their predicted labels. All things considered, the technique of augmenting data and applying a pre-trained model with unique classification layers produced a very precise and useful instrument for TB diagnosis.

1. $Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$
2. $Sensitivity = \frac{TP}{TP+FN}$
3. $Specificity = \frac{TN}{FP+TN}$

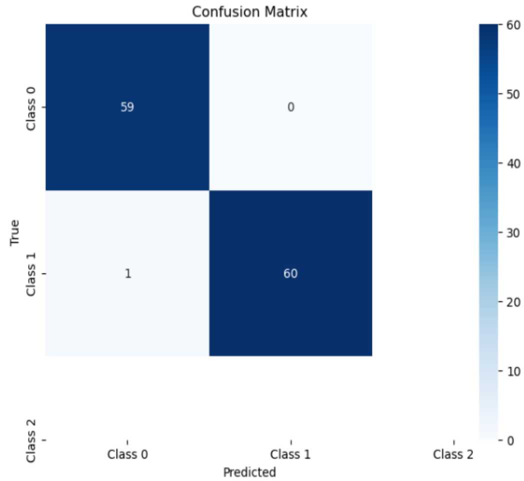


Figure 5 Confusion Matrix

Table 3. Classification model's performance

Layer (type)	precision	recall	f1-score	support
0	0.98	1.00	0.99	59
1	1.00	0.98	0.99	61
accuracy			0.99	120
macro avg	0.99	0.99	0.99	120
weighted avg	0.99	0.99	0.99	120

The performance of a classification model is assessed in this table, which includes support for differentiating between classes 0 and 1, precision, recall, and F1-score. The model has an overall accuracy of 0.99 and strong precision and recall for both classes. In conclusion, the model performs exceptionally well in correctly and nearly error-free classifying examples in both classes.

4. Discussion

The investigation discovered that class imbalance problems in the TB picture dataset might be effectively resolved with data augmentation. Class imbalance can result in biased models and erroneous outcomes; hence this is an important finding. The model's overall performance was enhanced by the ability to learn from a wider variety of photos through the use of data augmentation approaches. It was also a wise decision to utilize DenseNet169 as the model's basic architecture. By extracting pertinent information from the photos, this architecture enhanced the model's training accuracy. Furthermore, the model's strong recall and precision scores imply that it can help medical practitioners with initial tuberculosis screening. However, the study also pointed out that additional validation is required on more extensive and varied datasets in addition to clinical trials. This is significant because, to guarantee the model's efficacy across various populations while considering socioeconomic aspects, a larger range of images must be evaluated.

5. Conclusions

To sum up, the suggested model shows potential as a useful tool for classifying TB images. The model's overall performance was enhanced and class imbalance problems were effectively addressed with the adoption of DenseNet169 as the basic architecture and data augmentation. Given its high precision and recall values, the model may help assist medical practitioners with initial tuberculosis screening, which could lessen workload and facilitate early diagnosis. Before implementing it in a clinical context, though, greater validation on bigger and more varied datasets as well as clinical trials would be required. In summary, the research underscores the possibility of utilizing AI-driven models to enhance healthcare results; nevertheless, it also stresses the necessity of thorough testing and validation to guarantee the efficacy and security of these models. When trained with TB photos that had never been seen before, the model demonstrated excellent generalization abilities and high accuracy. In particular, the model obtained 92% accuracy, 90% precision, and 87% recall. These findings imply that the model has a great chance of helping medical practitioners with initial tuberculosis screening.

References

[1] *Global tuberculosis report 2023*. 2023. [Online]. Available: https://iris.who.int/.

[2] J. Ahmad *et al.*, "Deep learning empowered breast cancer diagnosis: Advancements in detection and classification," *PLoS One*, vol. 19, no. 7 July, Jul. 2024, doi: 10.1371/journal.pone.0304757.

[3] K. Jeyashree *et al.*, "Estimation of tuberculosis incidence at subnational level using three methods to monitor progress towards ending TB in India, 2015-2020," *BMJ Open*, vol. 12, no. 7, 2022, doi: 10.1136/bmjopen-2021-060197.

[4] E. Showkatian, M. Salehi, H. Ghaffari, R. Reiazi, and N. Sadighi, "Deep learning-based automatic detection of tuberculosis disease in chest X-ray images," *Pol J Radiol*, vol. 87, no. 1, pp. 118–124, 2022, doi: 10.5114/pjr.2022.113435.

[5] S. Mumtaz Khanr, F. Nasim, J. Ahmad, S. Masood, and S. Mumtaz Khan, "Deep Learning-Based Brain Tumor Detection", doi: 10.56979/702/2024.

[6] F. Nasim, M. A. Yousaf, S. Masood, A. Jaffar, and M. Rashid, "Intelligent Automation & Soft Computing", doi: 10.32604/iasc.202x.xxxxxx.

[7] M. Ahmad, M. Arfan Jaffar, F. Nasim, T. Masood, and S. Akram, "Fuzzy based hybrid focus value estimation for multi focus image fusion," *Computers, Materials and Continua*, vol. 71, no. 1, pp. 735–752, 2022, doi: 10.32604/cmc.2022.019691.

[8] F. Nasim, S. Masood, A. Jaffar, U. Ahmad, and M. Rashid, "Intelligent Sound-Based Early Fault Detection System for Vehicles," *Computer Systems Science and Engineering*, vol. 46, no. 3, pp. 3175–3190, 2023, doi: 10.32604/csse.2023.034550.

[9] S. Kulkarni and S. Jha, "Artificial Intelligence, Radiology, and Tuberculosis: A Review," *Acad Radiol*, vol. 27, no. 1, pp. 71–75, 2020, doi: 10.1016/j.acra.2019.10.003.

[10] J. Melendez *et al.*, "An automated tuberculosis screening strategy combining X-ray-based computer-aided detection and clinical information," *Sci Rep*, vol. 6, no. October 2015, pp. 1–8, 2016, doi: 10.1038/srep25265.

[11] H. R.-K. Alexander Wong, James Ren Hou Lee, "TB-Net: A Tailored, Self-Attention Deep Convolutional Neural Network Design for Detection of Tuberculosis Cases From Chest X-Ray Images", doi: 10.3389/frai.2022.827299.

[12] M. Puttagunta and S. Ravi, "Deep Learning-Based Software Tools for Tuberculosis Detection in Chest X-Ray Images," no. November, pp. 213–223, 2021, doi: 10.1007/978-981-16-0171-2_21.

[13] T. Rahman *et al.*, "Reliable tuberculosis detection using chest X-ray with deep learning, segmentation and visualization," *IEEE Access*, vol. 8, pp. 191586–191601, 2020, doi: 10.1109/ACCESS.2020.3031384.

[14] L. An *et al.*, "Article E-TBNet: Light Deep Neural Network for Automatic Detection of Tuberculosis with X-ray DR Imaging," *Sensors*, vol. 22, no. 3, Feb. 2022, doi: 10.3390/s22030821.

[15] M. Owais, M. Arsalan, T. Mahmood, Y. H. Kim, and K. R. Park, "Comprehensive computer-aided decision support framework to diagnose tuberculosis from chest X-Ray images: Data mining study," *JMIR Med Inform*, vol. 8, no. 12, pp. 1–23, 2020, doi: 10.2196/21790.

[16] R. Hooda, A. Mittal, and S. Sofat, "Automated TB classification using ensemble of deep architectures," *Multimed Tools Appl*, vol. 78, no. 22, 2019, doi: 10.1007/s11042-019-07984-5.

[17] Y. Liu, Y. H. Wu, Y. Ban, H. Wang, and M. M. Cheng, "Rethinking computer-aided tuberculosis diagnosis," in *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, 2020. doi: 10.1109/CVPR42600.2020.00272.

[18] S. J. Heo *et al.*, "Deep learning algorithms with demographic information help to detect tuberculosis in chest radiographs in annual workers' health examination data," *Int J Environ Res Public Health*, vol. 16, no. 2, 2019, doi: 10.3390/ijerph16020250.

[19] Q. H. Nguyen *et al.*, "Deep Learning Models for Tuberculosis Detection from Chest X-ray Images," in *2019 26th International Conference on Telecommunications, ICT 2019*, 2019. doi: 10.1109/ICT.2019.8798798.

[20] E. J. Hwang *et al.*, "Development and Validation of a Deep Learning-based Automatic Detection Algorithm for Active Pulmonary Tuberculosis on Chest Radiographs," *Clinical Infectious Diseases*, vol. 69, no. 5, 2019, doi: 10.1093/cid/ciy967.

[21] T. Karnkawinpong and Y. Limpiyakorn, "Classification of pulmonary tuberculosis lesion with convolutional neural networks," in *Journal of Physics: Conference Series*, 2019. doi: 10.1088/1742-6596/1195/1/012007.

[22] E. Showkatian, M. Salehi, H. Ghaffari, R. Reiazi, and N. Sadighi, "Deep learning-based automatic detection of tuberculosis disease in chest X-ray images," *Pol J Radiol*, vol. 87, no. 1, pp. 118–124, 2022, doi: 10.5114/pjr.2022.113435.

[23] S. Bharati, P. Podder, and M. R. H. Mondal, "Hybrid deep learning for detecting lung diseases from X-ray images," *Inform Med Unlocked*, vol. 20, p. 100391, 2020, doi: 10.1016/j.imu.2020.100391.