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Abstract

Tuberculosis (TB) remains a major public health challenge globally, and its burden is particularly pronounced in the Kyrgyz Republic, where the prevalence of multi-drug resistant (MDR) TB is high. This study aims to enhance early detection of TB by developing a Convolutional Neural Network (CNN) model trained on chest X-ray (CXR) images. Due to the lack of well-labeled CXR datasets in Kyrgyz hospitals, our research utilized an open dataset of TB and normal CXR images to train and validate the model. One of the challenges was the imbalance in the target class. To tackle this problem, we computed the class weights. We developed two models from scratch: the first one without class weights, and the second one implemented with class weights. Our class weights improved the performance of the model, which achieved 97% accuracy, 94% sensitivity, 98% specificity, 88% precision and 91% F1 score. Our results demonstrate the potential of CNN-based approaches in TB diagnosis and highlight the importance of data infrastructure enhancement for advancing TB care in the Kyrgyz Republic.

Keywords: Tuberculosis, Chest X-Ray, Convolutional Neural Network, Kyrgyz Republic, Binary Classification

1 Introduction

Among the most prevalent diseases in the world that spreads quickly and causes a great deal of illness is tuberculosis (TB), triggered by Mycobacterium tuberculosis, a bacteria that specifically affects human lungs [1]. There are the following types of TB: multi drug-resistant (MDR), pre-extensively drug-resistant (Pre-XDR), and extensively drug-resistant (XDR) [2]. Even though TB is generally treatable [3], prior to the coronavirus (COVID-19) pandemic, TB was the most common infectious agent-related cause of death, surpassing HIV/AIDS [4]. Following the COVID-19 pandemic, in 2022, TB ranked as the second most common cause of death worldwide [5]. According to the Global Tuberculosis Report 2023 by the World Health Organization (WHO) [5], the overall number of TB-related deaths worldwide in 2022 (including those among HIV-positive individuals) was 1.30 million (range 1.18–1.43 million). Further, a high prevalence of MDR TB in the Kyrgyz Republic is outlined in the report. By 2030, WHO aims to decrease the incidence and mortality rates from TB by 80% and 90%, respectively [6]. The foundation of their strategy is the early diagnosis and prompt treatment of TB patients.

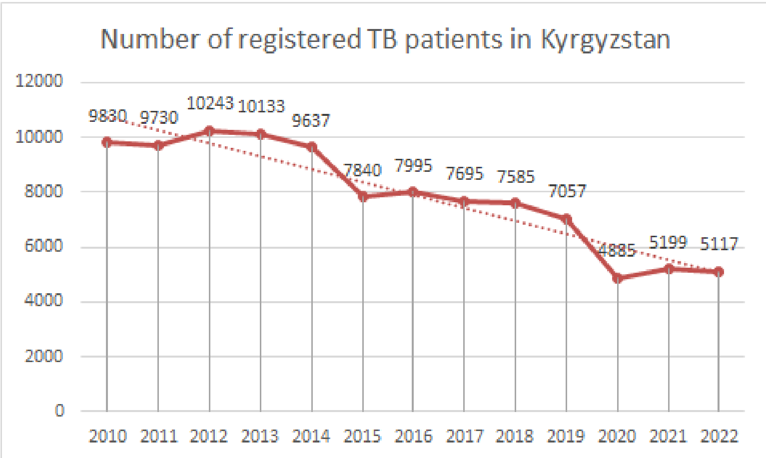

Fig. 1

In the figure 1 the number of registered TB patients in the Kyrgyz Republic from 2010 to 2022 is displayed. This line chart is generated via EXCEL program from the dataset "Number of morbidity of patients by active tuberculosis by types and territory" [7]. Although it shows a decreasing trend, we are still far from achieving "The END TB" goal.

The burden of TB in the Kyrgyz Republic in 2022 was 130 (range 106-152) rate per 100 000 population, with a total number of 8600 (range 7100-10 000) incidents, among which there were 3000 (range 2400-3600) MDR TB incidences and 240 (range 190-310) HIV-positive TB incidences. HIV-negative TB mortality rate amounted to 5.9 (range 5.2-6.7) per 100 000 population, with a total number of 390 (range 350-440) deaths, while HIV-positive TB mortality rate was 1.5 (range 0.85-2.3) with 98(range 56-150) deaths [8].

Factors such as stigma, the prevalence of drug and alcohol abuse and addiction, the presence of neglected groups, the difficulty that migrants and the homeless have in accessing healthcare facilities, and the relatively widespread use of either hospitalized models of care or alternative medicine add to the challenges healthcare systems encounter in correctly and quickly diagnosing tuberculosis cases [9]. Istamov et al. [10] conducted research on differences in TB treatment and its outcomes among migrants and non-migrants in the Kyrgyz Republic. One of the findings of their work was the high rate of internal (intra-country) migrants with MDR, while delayed treatment is higher among external (inter-country) migrants due to a lack of access to public health systems. The prevalence of TB seriously threatens public health in the Kyrgyz Republic.

The research work of Sakmamatov et al. [11] states that early detection of TB is essential to achieve excellent treatment outcomes. In this regard, the integration of advanced technologies, specifically deep learning, offers a promising path for improving the accuracy and efficiency of early TB diagnosis. Deep learning, a subset of artificial intelligence (AI), has shown impressive results in a number of fields, including medical picture analysis. Deep learning models, in particular Convolutional Neural Networks (CNNs), can be trained to interpret Chest X-ray (CXR) pictures and help identify anomalies related to TB. To our knowledge, there hasn't been any such work published in the Kyrgyz Republic. Thus, this study proposes the use of CNN in the detection of TB from CXR images.

2 Research Problem

The primary objective of this research is to develop a CNN model tailored for the detection of TB from CXR images.

i. Investigate the feasibility and effectiveness of utilizing deep learning technology, specifically CNNs, in enhancing the early detection of TB.
ii. Assess the performance of the developed CNN model in terms of sensitivity, specificity, precision, F1-score and overall accuracy.
iii. Address the challenges faced in the development of CNN model within the context of the Kyrgyz Republic.

By achieving these objectives, this research aims to contribute valuable insights to overcome challenges and advancements in the field of TB diagnosis in the Kyrgyz Republic, with the ultimate goal of improving healthcare practices and outcomes, especially in regions with a high burden of the disease.

This research work is divided into six sections. In Section 1, the introduction focuses on the threat of TB in the world and the Kyrgyz Republic. In Section 2 the research problem is discussed. Section 3 covers a review and analysis of related literature. Section 4 provides the methodology used in this study. In Section 5 the results of the research are presented. Section 6 discusses the obtained results and obstacles in building the model. Section 7 concludes the findings of the study and future work is discussed.

3 Literature review

In this section, we will introduce related research works with a review and analysis of their solutions and strategies.

Liu et al. [12] proposed the use of CNN based on the architectures of AlexNet [13] and GoogLeNet [14] for the classification of various types of TB. They utilized a dataset from "Socios en Salud", Partners In Health in Lima, Peru. The dataset contains 4701 CXR images: 453 normal (no TB) and 4248 abnormal (has TB). To deal with a clear imbalance in the target classes, they applied a shuffling technique that increased the performance of their models in predicting all TB manifestations. The best accuracy they obtained was 85.65% for AlexNet. This study also highlighted a lack of large medical datasets with high-quality images, which leads to restrictions in training the CNN model. To overcome this obstacle, the authors adopted a pre-trained model from the ImageNet dataset [15].

Hooda et al. [16] presented their solution to classify TB using an ensemble of three CNN architectures, including AlexNet, GoogLeNet, and ResNet-34 [17]. This study has collected CXRs from various datasets, acquiring 1133 images in total. The authors fine-tuned all three models for TB detection and trained them separately at the beginning with the appropriate values of the hyperparameters for each model. In the next step, they combined the models into an ensemble with the help of a fusion technique. The authors reported the performance of AlexNet, GoogLeNet, and ResNet-34 to be 83.56%, 80.59%, and 84.12% accuracy respectively. The proposed ensemble outperformed each model's result, achieving 88.24% accuracy. The research work concludes that the developed model would assist radiologists in the analysis and final diagnosis of TB from CXRs.

In a comprehensive research conducted by Liu and Huang [18], six different CNN models, namely DenseNet121 [19], Inception V3 [20], NASNet mobile [21], Resnet50 [17], Vgg16 [22], and Xception [23], were evaluated and analyzed. Their introduced dataset of CXR photos, labeled by certified doctors of Chinese and American hospitals, consists of 800 pictures, 394 of which are TB and 406 are not TB. For all models, a sigmoid function was implemented as an activation function in place of a step function, because finding the derivative of the sigmoid function requires less computing than calculating the derivative of the step function. The authors have chosen a binary cross-entropy function for six models as an alternative to the typical quadratic cost function, resulting in faster learning of models and more accurate classification. In this study, Stochastic Gradient Descent (SGD) was applied as a gradient descent algorithm. After thorough experimentation, DenseNet was discovered to be the best model with 83.5% accuracy, whereas Xception's performance was the worst, obtaining only 78.6% accuracy.

Sundari et al. [24] in their research work introduced Optimized Sequential AlexNet (OSAN) architecture for TB prediction. "Tuberculosis (TB) Chest X-ray Database" had been used in their study [25]. Among the 3600 medical images, 3000 were normal and 600 were TB-positive. They used class weights to address the class imbalance, which they identified as a common concern in most real-world scenarios. The class weights technique assigns more weight to minority classes. During the training phase, the loss associated with the minority class was multiplied by a factor of five, increasing their impact on model parameter updates. The suggested OSAN architecture's innovations are the following:

i. Adaptive Average Pooling layer instead of fixed-size pooling layer, has enabled the model to capture features of TB from CXR photos more efficiently.
ii. Freezing of Pre-trained Layers method was implemented in seek of balancing transfer learning and fine-tuning of the model.
iii. Customized Classifier was built to execute binary classification.

The overall obtained accuracy was 99.67%.

Maheswari et al. [26] suggested the Shallow-CNN (S-CNN) model, which has relatively fewer layers compared to classical CNN models. According to the authors, most Deep Neural Networks (DNN), especially being pre-trained, perform excellently in classification. However, the price of such high accuracy is the inability to interpret why they fail in other cases, leading to a dilemma between interpretability and accuracy. To avoid this constraint, S-CNN was built. The study made use of the "Tuberculosis (TB) Chest X-ray Database", which was already mentioned before. They split the data into 3 groups: a training set with 750 images, a testing set, and validation sets with 125 pictures in each of them. The proposed model's architecture comprises four convolution-maxpooling layers that include different hyperparameters, which were updated for the model to perform the best using a Bayesian optimization technique. All these efforts led to an achievement of 95% accuracy and F1-Score correspondingly, comparable results to DenseNet, whose results were 91% for accuracy and F1-Score.

Zhang et al. [27] conducted a meta-analysis of studies from the PubMed, Web of Science, Embase, Scopus, MEDLINE, and CINAHL databases that were published during the 2013-2023 period and focused on the implementation and success of AI in TB treatment. After the filtering process, 25 relevant studies were admitted for review. Their review highlights encouraging results of AI-enabled models, including CNN, in the prediction of TB and treatment duration by utilizing imaging, sociodemographic, clinical, and genomic data. The authors outline the importance of developing an AI-enabled system with the consideration of ethics, data privacy, transparency of the deployed system, compliance with medical standards, and constant refinement of its performance. They conclude that the utilization of AI offers promising prospects in enhancing treatment practices of TB.

We presented research works that proposed various solutions for detecting TB from CXR. CNN has proven to be feasible and efficient in tackling this difficult task, and several CNN architectures were analyzed. We reviewed diverse techniques and strategies for handling a lack of large and high-quality CXR datasets and target class imbalance. Finally, we established the necessity and potential of further research and development of AI-enabled systems for improving TB treatment.

4 Methodology

4.1 Dataset

This study adopted the open dataset "Tuberculosis (TB) Chest X-ray Database" [25]. It includes 4200 CXR images, 3500 of them are labeled as normal and 700 are TB.

All CXRs are in Portable Network Graphics (PNG) file format. The size of each image is 512×512 pixels. All the images are in the format of RGB with three channels (Red, Green and Blue), each channel comprises pixels that represent shades of the respective color. However, we can find gray-scale images, which were saved as RGB. All private information has been deleted from the images in accordance with ethical considerations and data privacy. The percentage of TB images is 16.67%, whereas normal images amount to 83.33%, leading to the imbalance of the target class. Figures 2 and 3 demonstrate the samples of Normal and TB CXRs.

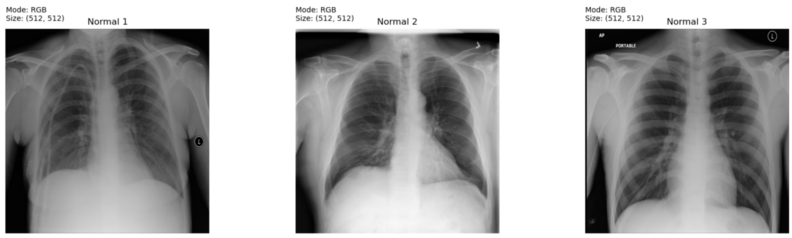

Fig. 2: Sample of Normal CXRs

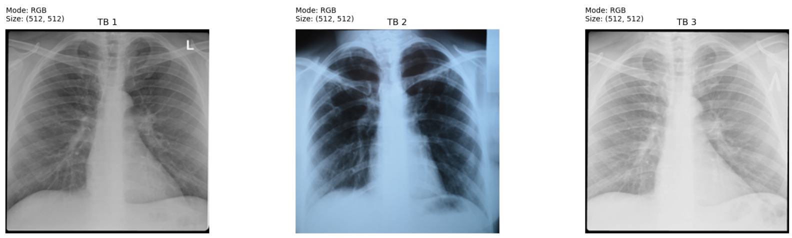

Fig. 3: Sample of TB CXRs

4.2 Data Preprocessing

Data preprocessing is a critical stage that involves modifying and transforming data before it is used by a model. We experimented with resizing images to 32×32 and 64×64, which resulted in a low quality of images, leading to a loss of important features (pixels) that CNN would use for prediction. Thus, we discovered that the optimal solution is to resize all images to 128×128 size. After that, we converted all CXRs from RGB format to gray-scale, decreasing the number of pixels from 3 channels to 1, which reduced the computational time. We transformed the images into numpy arrays, obtaining two sets: "normal" with the shape of (3500, 128, 128) and "tb" with the (700, 128, 128) shape. As pixel's value varies from 1 to 255 in the gray-scale mode, we normalized each array by dividing by 255.

4.3 Data Splitting

The dataset was randomly split into training, testing and validation sets. Training set contains 70% of the original dataset, while testing and validation sets each cover 15%. This allowed us to include a reasonable amount of normal and TB samples in each set. We labeled normal CXRs as class 0 and TB images as class 1. The details are displayed in the figure 4.

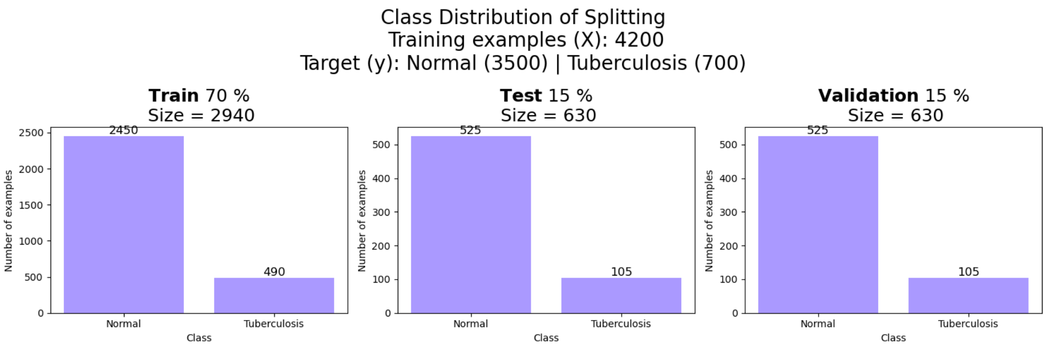

Fig. 4: Data Splitting

4.4 Handling the Class Imbalance

Class imbalance is an obstacle that can prevent our CNN model from training properly, mainly affecting its performance. To tackle this issue, we developed our formula to calculate class weights w_0 for class 0 and w_1 for class 1:

$$w_0 = \frac{N}{N_0} \times k$$

$$w_1 = \frac{N}{N_1} \times k,$$

where

- N_0 is the number of samples in class 0,
- N_1 is the number of samples in class 1,
- N is the total number of samples, $N = N_0 + N_1$.
- k is a scaling factor, set to 0.5 for balanced impact.

These weights are inversely proportional to the frequency of the respective class in the dataset, scaled by a factor of 0.5. This means that the more frequent class gets a smaller weight, and the less frequent class gets a larger weight, thereby compensating for the imbalance during model training. This helps ensure that the minority class 0 has a higher influence on the model training process compared to the majority class 1, preventing the model from neglecting the minority class. We obtained the following values for our class weights: $w_0 = 0.6$ and $w_1 = 3$.

4.5 CNN Architecture

In this study, we developed our CNN model based on the architecture of AlexNet [13]. It consists of 5 convolutional layers,3 fully connected layers, and the output layer:

i. **Convolutional Layers:** The first convolutional layer comprises 96 filters with a kernel size of 11x11 and a stride of 4, utilizing the Rectified Linear Unit (ReLU) activation function defined by the following equation:

$$\mathrm{ReLU}(x) = \max(0, x) \tag{1}$$

Subsequent convolutional layers consist of 256 filters of size 5x5 and 384 filters of size 3x3. Each convolutional layer is followed by max-pooling layers of size 3x3 and strides of 2.

ii. **Fully Connected Layers:** Following the convolutional layers, the feature maps are flattened and passed through three fully connected layers. The first two fully connected layers consist of 4096 neurons each, with ReLU activation functions and Dropout regularization with a rate of 0.4 applied to mitigate overfitting. The third fully connected layer includes 1000 neurons, also with a ReLU activation function.

iii. **Output Layer** employs a sigmoid activation function to produce binary classification probabilities for 2 classes. The sigmoid activation function is defined as follows:

$$\sigma(z) = \frac{1}{1 + e^{-z}} \tag{2}$$

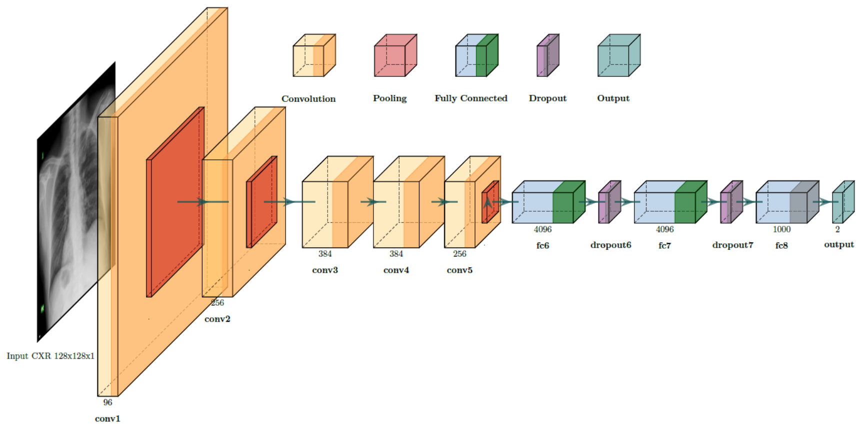

Fig. 5: Architecture of AlexNet for TB detection

The model was compiled using the Adam optimizer with the 0.001 learning rate. The loss function for training was binary cross-entropy, suitable for binary classification tasks. The model was trained for 30 epochs.

4.6 Evaluation Metrics

We applied the following metrics to assess the performance of our CNN model:

i. **Accuracy:** It is the ratio of correctly predicted CXR images to the total number of predicted CXRs, defined by the following equation:

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \times 100, \tag{3}$$

where

- TP (True Positive) is the number of TB CXR images correctly predicted as TB.
- TN (True Negative) is the number of Normal CXR images correctly predicted as normal.
- FP (False Positive) is the number of Normal CXR images incorrectly predicted as TB.
- FN (False Negative) is the number of TB CXR images incorrectly predicted as normal.

ii. **Sensitivity (also known as Recall):** It is the ratio of correctly predicted TB images to the total number of TB images, defined as follows:

$$\text{Sensitivity (Recall)} = \frac{\text{TP}}{\text{TP} + \text{FN}} \times 100 \tag{4}$$

iii. **Specificity:** It is the ratio of correctly predicted normal images to the total number of normal images, computed by the next formula:

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}} \times 100 \tag{5}$$

iv. **Precision:** It is the ratio of correctly predicted TB images to the total number of images that were predicted as TB:

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \times 100 \tag{6}$$

v. **F1 score:** It is the harmonic mean of Precision and Recall, defined by the following formula:

$$\text{F1 Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Precision}} \tag{7}$$

5 Experimental and Results

We have trained our CNN model from scratch. At first, the model was trained without implementing the class weights. The obtained accuracy was 83%, however, other metrics showed low values. In the second training phase, we included the class weights in the model. It strongly boosted the performance of the model, and this time the confusion matrix showed that the model was predicting both classes. The model has achieved an accuracy of 97%, sensitivity of 94%, specificity of 98%, precision of 88% and F1 score of 91%. Figure 6 demonstrates the accuracy and loss of the model over epochs with class weights included and Figure 7 displays the confusion matrices for Train and Test sets. In Table 1 the performance metrics of two models with class weights and without class weights are shown.

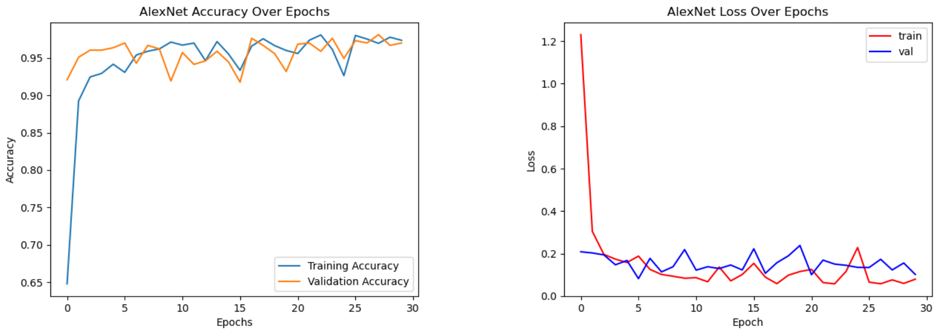

Fig. 6: Accuracy and Loss over Epochs

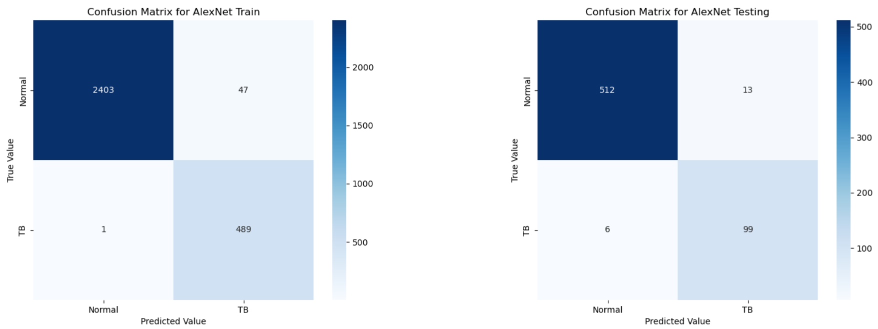

Fig. 7: Confusion Matrices for Train and Test Sets

Table 1: Model Performance Metrics

Class Weights	Accuracy	Sensitivity	Specificity	Precision	F1 Score
Not Included	83%	0%	100%	0%	0%
Included	97%	94%	98%	88%	91%

6 Discussions

Our CNN model without class weights obtained 83%, which seems a decent result at first glance. However, after inspection of the confusion matrix and other metrics, it was discovered that the model was only predicting class 1 and neglecting class 0. Because of the prevalence of class 1, the calculated accuracy was high, which may result in misleading inference. Other metrics should be reviewed to assess a model objectively. Thus, sensitivity and precision of 0% clearly show the inability of the model to identify TB images. This version of the model is not suitable for TB detection in the case of class imbalance.

The inclusion of the class weights improved the model's prediction ability by a great margin. Sensitivity of 94% and specificity of 98% tells us that the model predicts both TB and normal images, respectively, with a high probability. Precision reveals that 88% of the model's predictions of CXRs as TB are correct, while the rest of 12% are misclassified as TB. F1 Score of 91% demonstrates that the model's predictions of both TB and normal images are highly accurate, i.e. the model is balanced for both classes. Our class weights contributed to the overcoming of class imbalance and enhancing the CNN's performance in both classes 0 and 1, making it a suitable model to detect TB from CXR.

We discovered the lack of well-labeled datasets of CXR images in hospitals of the Kyrgyz Republic, which put limitations to our research at this stage. According to Sakmamatov et al. [11], it is crucial to reorganize the hospital case records in the Kyrgyz Republic with a more structured recording of TB cases as it will allow future researchers to gather more detailed information about TB patients. Shauer et al. [28] in their study conclude that the incorporation of an electronic TB register system may contribute to the advancements in TB care in the Kyrgyz Republic. In addition, our study suggests improving monitoring databases in the Kyrgyz hospitals to open new opportunities for future studies, allowing them to collect more CXR datasets for further development of CNN models to detect TB in the context of the Kyrgyz Republic, specifically adjusting models to identify MDR TB, as its prevalence in the country was previously highlighted.

7 Conclusion and Future Works

Our proposed CNN model has successfully provided impressive results in TB detection from CXR images. We overcame the problem of class imbalance with the help of our class weights, which improved the model's performance by a great margin compared to the one without class weights. Thus, the model achieved 97% accuracy, 94% sensitivity, 98% specificity, 88% precision and 91% F1 score. The feasibility and effectiveness of the CNN model in the TB classification promise significant improvements in the early diagnosis of TB in the Kyrgyz Republic, which will lead to better treatment with more probability of a successful cure from the disease, and achieve the ultimate goal of reducing both the number of TB cases and mortality rate.

Our study also addresses the challenges in developing the CNN model specifically for the Kyrgyz Republic. Due to the absence of well-structured databases of CXR images in the Kyrgyz hospitals, our research was limited to available open dataset. Our study emphasizes the importance of restructuring hospital TB case records. Enhanced databases will open new avenues for future studies related to the development of AI-enabled models for TB prediction and more accurate analysis of TB cases and patients in the Kyrgyz Republic.

The future work in this field will be the collection of CXR images from the hospitals in the Kyrgyz Republic. Collaboration with health experts would be required to label these images and divide them into classes. Future studies will focus on utilizing a pre-trained AlexNet model to increase classification performance and minimize the number of misclassifications by increasing precision and sensitivity. Furthermore, we aim to train our model for the detection of various types of TB, especially MDR TB, which dominates in the country.

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