International Journal for Multidisciplinary Research (IJFMR)
E-ISSN: 2582-2160 ● Website: www.ijfmr.com ● Email: editor@ijfmr.com

Systematic Literature Review: An Intelligent Pulmonary TB Detection from Chest X-Rays

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Abstract
Tuberculosis (TB) is one of the top ten reasons for death from an infectious agent. Although TB is curable and preventable, delay in diagnosis and treatment can lead the patient to death. Advancements in computer-aided diagnosis (CAD), particularly in medical images classification, significantly contribute to early TB detection. The current state- of-art CAD for medical images classification applications using a method base on deep learning techniques. The problem faced in this deep learning technique is that, in general, it only uses a single modal for the model. In contrast, in medical practice, the data used for TB analysis not only focuses on images but also includes clinical data such as demographics, patient assessments, and lab test results. This systematic literature review describes different deep learning methods using single modal or multimodal techniques that combined images with other clinical data. We conducted a systematic search on Springer, PubMed, ResearchGate, and google scholar for original research leveraging deep learning for Pulmonary TB detection.

Keywords: tuberculosis, deep learning, transfer learning, CNN, CAD, single modal, multimodal

1. INTRODUCTION

Tuberculosis (TB) is a global health problem. According to the WHO Global Tuberculosis Report 2020, TB is a significant cause of ill death and one of the leading top 10 causes of death worldwide. Indonesia itself is the second- largest endemic with 8.5 % of the global total. TB was the leading cause of death in some developing countries. Therefore the need to improve TB diagnosis and detection is clear.

One of the best ways to diagnose TB is through a sputum culture test. Still, this kind of test could take 1 to 8 weeks to provide results. Therefore, needed an early diagnosis to increase treatment success. Through medical imaging and deep learning methods, a radiologist could examine patient lung images taken from an X-Ray machine to detect TB with high accuracy and time efficiency.

Compared to a sputum examination, CAD has a short detection time and can be classified once the image is inserted into the application. There are several algorithms applied to CAD for image classification, especially for TB detection. For instance, conventional machine learning algorithms such as Simple Linear Regression, k-Nearest-Neighbours (kNN), Sequential minimal optimization, Support Vector Machine (SVM), to name but a few or more advanced techniques called deep learning. However, conventional machine learning has a limitation when extract differentiating features from the training set of data. This limitation has been covered with advances in deep learning, especially in Convolutional

Neural
Network (CNN) [1]. Therefore, to date, conventional machine learning approaches are no longer use for image classification. The CNN's superior performance compared to other traditional recognition algorithms and the ability to extract features from images makes CNN the first choice to solving a complex medical image classification problem. In pulmonary TB detection from X-Ray Images, CNN methods have proven very effective and achieved a range of high-quality diagnostic solutions. However, in modern medical practice, especially in TB detection, use images as the only input source is not commons. There are other clinical data used, such as lab
results, patient demographics, and patient assessments.

Fortunately, the CNN model can be combined with other models that process clinical data inputs other than images. Several researchers have successfully applied this model with promising performance improvements. Therefore, this systematic review presents the current CNN method with various additional techniques to increase model performance, such as augmentation, segmentation, transfer learning, and a multimodal approach that uses CNN along with other clinical data.

2. REVIEW METHODOLOGY

A search strategy was done by identifying recent related published articles from Google scholar, Springer link, and PubMed for recent related studies for the data sources. There were many approaches for literature review. One of them is through systematic literature review (SLR). This approach is divided into four stages, starting from determining the database source and conducting queries based on research topics as used by Maniah et al. [1].

The first stage is defined the research question. The main research question in this study is “what are the methods for pulmonary TB detection?”. Based on the research question, queries were determined as input to multiple data sources used in this study.

The second stage is identifying titles by applying inclusion criteria and exclusion criteria. The inclusion criteria are paper using artificial intelligence (AI) method or chest X-Ray images, and exclusion criteria are any paper not within inclusion criteria. Several words are using for a query, such as: “Pulmonary Tuberculosis,” “Deep Learning,” Convolutional neural network,” “Detection,” “Diagnosis,” “Ensemble,” “Multimodal” combined with “AND” and “OR” in the search string. We included all published studies that use deep learning techniques to analyze and classified TB from Chest X-Ray images. We also included some research on biomedical photos using deep learning techniques.

The third stage is a review by reading abstract content and keywords. Again, only content related to pulmonary TB using deep learning or convolutional neural network method and 978-1-6654-4002-8/21/$31.00 ©2021 IEEE several other techniques such as ensemble, transfer learning, and multimodal were selected. We further select studies based on the methods were used and accuracy performance as well. After content filtering, we conducted an assessment of the paper by reading and rereading the whole study. Diagnostic accuracy measures including sensitivity, specificity, and AUC were reported when available. We also reported the type of dataset used and how the algorithm of the proposed study method was executed. The following is done by determining a task following the research topic and then extracting specific details such as author and year published, input data type, approach, datasets, and model performance, then summarized in one research report. The whole process of this literature review is shown in Figure 1.

3. RESULTS AND DISCUSSION

Through this systematic review, a total of 1310 studies were identified. After reviewing the complete text, a total of 15 studies were extracted as a final review. The majority of the studies used convolutional neural networks with both Shenzhen and Montgomery datasets [2]. 14 out of 15 studies consider only image data as an input, and we categorized these approaches as a single modality. One of their approach using multimodal techniques consider images and demographics variable as an input. Another study by Yahiaoui et al. [3] using SVM with 38 properties extracted from patient discharge summary, this method obtains an Accuracy of 96.68%.

Unlike previous researchers who used the conventional machine learning method, in this research, Sathitratanacheewin et al. [4] developed a TB detection model that uses a deep learning method. Shenzhen and ChestX-Ray8 [5] datasets were used in this study. The Shenzhen dataset contains 662 X-ray images with 336 patients confirmed positive, and 326 patients proved negative for TB. Unlike the Shenzhen data set, ChestX-Ray8 datasets only consist of lung abnormalities such as atelectasis, cardiomegaly, effusion, infiltration, mass, nodule, pneumonia, and pneumothorax without TB positive or negative information. Referring to the WHO guideline, the abnormality in the chest with infiltration, pneumonia, atelectasis, and effusion can be categorized as TB positive. With no pre-trained model involved, this model achieves a decent Area under the curve (AUC) score of 0.705-0.9845.

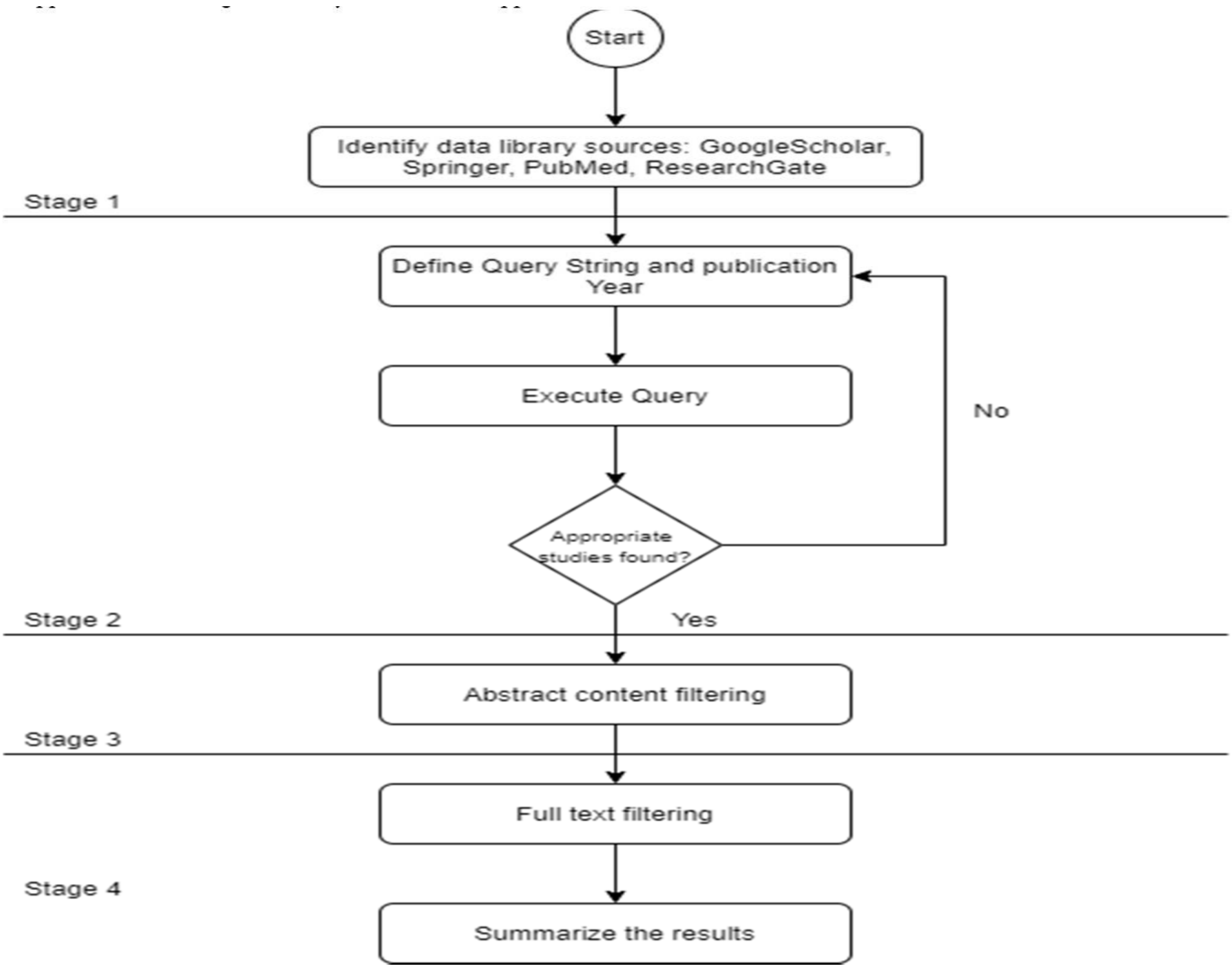

Figure 1. Review Methodology

It has been known that deep learning algorithms, such as CNN, typically achieve the best performance on large datasets. This fact has been shown by Oloko-Oba et al. [6] for the case of Chest X-Ray, which tried to use only the Montgomery dataset. They realized that this small dataset would lead to overfitting. Therefore, they performed data augmentation to increase images from 136 to 5000 images. Using 4 Conv layers and one fully connected layer, this model reached 87.1 % of accuracy.
Despite the requirement of a large dataset, deep learning can still achieve competitive performance with proper hyperparameter tuning. For instance, Lumbanraja et al. [7] showed that deep learning could perform well in a limited dataset for phosphorylation site prediction. To overcome the limitations of the datasets, they did hyperparameters tuning on learning rate, dropout rate, and l2 regularization to improve model performance. As a result, their method achieved a competitive AUC score of 0.92 on the tiny P.ELM datasets.
Another common technique to overcome the small dataset challenge is transfer learning, which uses pre-trained CNN on a large dataset to learn from the small dataset. For example, transfer learning was utilized by Haloi et al. [8] by fine-tuning a pre-trained model on Chest-Xray14 [5] for Tuberculosis and Pneumonia classification. With five different fine-tune architecture, this study reached an AUC of 0.949 for Tuberculosis classification. Meanwhile, Filho et al.
[9] used transfer learning on three datasets: Shenzhen, Montgomery, and PadChest [10], with pre-trained AlexNet [11], GoogleNet [12], and ResNet [13]. As a result, this study reached AUC from 0.78 to 0.84, sensitivity from 0.76 to 0.86, and specificity from 0.58 to 0.74.
Meraj et al. [14] also used transfer learning with four pre- trained CNN models such as GoogleNet, ResNet50, VGG- 16, and VGG19 were utilized on Shenzhen and Montgomery datasets. The highest performance obtained is 86.74% Accuracy and 92.0 AUC Score.
Transfer learning could also produce a decent performance when used on the different types of images, as Pardamean et al. [15] did in their study for learning Mammogram X-ray images. They carried out transfer learning from ChexNet [16], a model trained on 112,120 Chest X-ray images. This approach produces an accuracy rate of 90.38% on the DDSM dataset [17][18].
Not only X-ray images, but transfer learning also works well when applied to another type of medical image. Dominic et al. [19] did in their study by using a tiny data set from NYU for classifying autism spectrum disorders. Realize the limitation of the dataset. they applied the transfer learning method from InceptionResNetV2 [20] with ImageNet [21] pre-trained weights. With only 172 images, this method obtains 57.6% accuracy compared to other studies using 1992 patient images. The result obtained is only 2.4% different.
Transfer learning is not the only approach to improve the performance of Chest X-Ray models. For example, Sahlol et al. [22] combine Artificial Ecosystem-Based Optimisation
[23] and Pre-Trained MobileNet [24] model to achieve an accuracy of 90.23% on the Shenzhen dataset. On the other hand, Norval et al. [25] focussed on image preprocessing engineering such as Histogram Equalization, Contrast Enhancement, reduce color channels, sharpening, and ROI cropping to achieved an accuracy of 92.54%.
Another technique to improve the performance is called ensemble learning, which is the technique that combines several base models to produce one optimal predictive model.
This method was used by Guo et al. [26]. Six pre-trained models were involved in this study, including the likes of VGG16 [27], VGG19 [27], InceptionV3 [20], and ResNet34, ResNet50, and ResNet101. Along with the Artificial bee colony (ABC) algorithm for hyperparameter tuning, this study has reached

0.99 of AUC for chest abnormalities detection.
Ensemble deep learning also used by Hwa et al. [28] combined with the Canny edge detector technique for image preprocessing. According to researchers, canny edge detector techniques would increase the model's performance. With 92.05% Accuracy reached, they have proved their methods worked.
The ensemble method used by several previous researchers has been proven to improve. Research by Lakhani and Sundaram [29] also uses this technique. By only applying simple ensemble learning on Alexnet and GoogleNet, it can result in increased performance. Even though only slightly raised in AUC score, this technique is proven to produce a better model.
Images were used as input in all previously discussed methods. Heo et al. [30] used multimodal techniques to combine image data and demographics variables consisting of Age, Gender, Height, and Weight to making classifications. Image segmentation was performed in preprocessing step using U-Net [31] algorithm. This study conducted 6 pre-trained models such as: VGG19, InceptionV3, ResNet50, DenseNet121, and InceptionResNetV2. There was an increase in AUC of 0.0138 when adding demographic variables using concatenation techniques with the CNN model. The Results indicate multimodal techniques have shown promising performance. Table 1 displays a summary of included study and techniques.

Table 1. Summary of studies

Authors and Year Published	Input	Approach	Dataset	Performance
Yahiaoui et al., 2017	Patient Clinical History Features	Binary classifier using Support Vector Machine (SVM)	Diyarbakir Hospital, Turkey Database	The accuracy obtained is 96.68%
Sathitratanacheewin et al., 2020	CXR Images	CNN with augmentation techniques	Shenzhen and ChestX-Ray8	For Shenzhen, AUC is 0.8502 and for ChestXray-8, AUC is 0.7054
Oloko-Oba & Viriri, 2020	CXR Images	CNN and augmentation to replicate images from 136 to 5000 images to avoid overfitting	Augmented Montgomery dataset	The accuracy obtained is 87.1%
Haloi et al., 2018	CXR Images	CNN with modified Residual Inception Module	ChestXray-14 [5], Mendeley [32] Shenzhen, Montgomery, and Belarus	Sensitivity 0.925 Specificity 0.910 AUC 0.949
Colombo Filho et	CXR Images	AlexNet, GoogleNet,	Shenzhen,	**ResNet** Accuracy

al., 2020		and ResNet. Zooming, rotating, and flipping for image augmentation	Montgomery, and PadChest	67%, Sensitivity 0.76, Specificity 0.58 **GoogleNet** Accuracy 75%, Sensitivity 0.76, Specificity 0.74 **AlexNet** Accuracy 73%, Sensitivity 0.86, Specificity 0.60
Meraj et al., 2019	CXR Images	VGG16, VGG19, Resnet50, and GoogleNet	Shenzhen and Montgomery	For Shenzhen AUC obtained is 0.92 and for Montgomery AUC received is 0.90
Sahlol et al., 2020	CXR Images	Pre-Trained MobileNet with ImageNet weight and AEO feature selection	Shenzhen and own collected Dataset2	Shenzhen accuracy obtained is 90.23% Dataset2 Accuracy obtained is 94.1%
Norval et al., 2019	CXR Images	CNN with image preprocessing such as Histogram Equalization, contrast enhancement, reducing the color channel, sharpening, and taking the cropped ROI.	Shenzhen and Montgomery	The highest accuracy obtained is 92.54%
Guo et al., 2020	CXR Images	Pre-trained InceptionV3, VGG16, VGG19, Resnet34, ResNet50, ResNet101 with Automatic bee colony (ABC) algorithm for hyperparameter tuning. Linear Average Based Ensembling for final Output	Shenzhen and NIH	AUC Obtained is 0.99 for Shenzhen dan 0.976 for the NIH dataset, and this study only predicts chest abnormalities
Hwa et al., 2019	CXR Images	Ensemble InceptionV3 and VGG16 with Canny edge detector for image processing	Shenzhen and Montgomery	Accuracy 92.05%, Specificity 95.45%, Sensitivity 88.64%
Lakhani & Sundaram, 2017	CXR Images	Ensemble AlexNet and GoogleNet	Shenzhen, Montgomery, Belarus and	Highest AUC obtained is 0.99 on the Ensemble model.

			Thomas Jefferson	
Heo et al., 2019	CXR Images, Demographic variable	Multimodal with images and demographics variables as an input. Pretrained VGG19, InceptionV3, ResNet50, Densenet121, InceptionResNetV2	Korea Annual worker's health examination data	Highest AUC obtained is 0.9213 with a 0.0138 AUC increase compared to images only models. Highest AUC increases on the DenseNet121 model by 0.0288 points compared to the images-only model.

4. CONCLUSION

Through this systematic literature review, we have summarized several techniques and approaches. In the preprocessing image phase, segmentation and augmentation techniques are proven to obtain higher final prediction performance. On the other hand, CNN with ensemble received higher accuracy compared to a non-ensemble method. We also found that the multimodal approach that uses images and clinical data improves the performance over single modality models. The modern medical practice relies heavily on multiple sources of data to make treatment decisions, not least on the interpretation of medical images, where substantial clinical context is often essential for making diagnostic decisions [33].

Multimodal methods have been successful in improving models outside of medical images [34][35]. In modern clinical practice, images or clinical data alone are not sufficient for diagnosis. In tune with medical images, leveraging the multimodal method has proven effective in image recognition and classification, especially the multimodal combined with ensemble technique. Consistently showed performance improvements, future work should consider multimodal with ensemble techniques to solve pulmonary TB detection problem.

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