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Review Article

A Systematic Analysis of Tuberculosis prediction using Deep Learning Technique

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Abstract: Tuberculosis (TB) ranks among the top ten causes of death attributed to infectious agents globally. Despite being a curable and preventable disease, untimely diagnosis and treatment delays can result in fatal outcomes for patients. Notably, strides in computer-aided diagnosis (CAD), particularly in the classification of medical images, play a pivotal role in the early detection of TB. The current state-of-the-art in CAD for medical image classification relies on methods based on deep learning techniques. But one significant drawback of these deep learning methods is that they tend to model using only one modality. This is in sharp contrast to clinical practice, where photographs are only one aspect of the data used for tuberculosis analysis; other vital clinical data includes patient assessments, demographics, and laboratory test results. Addressing this disparity, our systematic literature review delves into various deep learning approaches, comparing those reliant on a single modality with those incorporating multimodal techniques. These multimodal techniques fuse image data with additional clinical information to provide a more comprehensive understanding of TB diagnosis. To compile this comprehensive review, we systematically searched databases including Springer, PubMed, ResearchGate, and Google Scholar for original research leveraging deep learning in the context of pulmonary TB detection. By elucidating the landscape of single modal and multimodal deep learning methods, our review aims to contribute valuable insights for researchers, clinicians, and stakeholders invested in advancing the state of TB diagnostic technology and improving patient outcomes.

Keywords: Tuberculosis; CAD; TB diagnosis; Early Detection of TB; chest X-ray; Deep Learning

1. Introduction

Since the 1940s, when early work on artificial intelligence began, there has been the hope that computers could assist humans in resolving issues [2] that interest them. This hope dates back to the beginning of AI itself. The number of scientific contributions connected to artificial intelligence skyrocketed after Alan Turing carried out the test that determines whether or not a machine is intelligent in the year 1950. This test bears Alan Turing's name. This gave rise to the field of automatic learning, which is to devise strategies enabling computers to acquire knowledge independently. One subfield of machine learning known as artificial neural networks involves teaching computers to learn and make decisions through interconnected artificial units (called "artificial neurons"). Deep learning, often referred to as DL, constitutes a subfield

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within machine learning where it harnesses computer architectures that are specifically designed to capture high-level abstractions within data, instead of relying on transformation-based approaches

The development of learning methods in conjunction with neural networks made this achievement attainable. Notation in matrices or tensors is used when the data is represented by multiple linear and iterative components. The processing of digital images is an example of an application that uses these methods. In recent years, the information and communications technology field has seen a rise in the significance of digital image processing. Consequently, it has become the basis for various areas, such as computer vision, remote sensing, space travel, and medical diagnostics. The process of modifying digital images with the assistance of a computer to either improve the images' quality or make them more searchable is referred to as "digital image processing" (or "DIP" for short). The Data Integrity Project (DIP) has developed into a highly specialized subfield within the field of computer science [3]. Many digital imaging and image processing techniques have become mainstream medical practice. The diagnosis of tuberculosis involves using digital image processing, just like the work done here. Consumption, also known as tuberculosis, is an infectious disease that can last long. Even though the lungs are the primary organ affected by bacteria, they can also affect other body systems. A person's actions can aid the transmission of tuberculosis through the air. If it is caught early enough, it can be prevented and treated; however, if it is not, it can be fatal. Taking an X-ray of the chest and growing bacteria from the sputum is one of the diagnostic procedures [4] that can be used for tuberculosis.

In accordance with data sourced from the Statistical and Death System [5], a database maintained by the General Directorate of Epidemiology, it has been determined that tuberculosis stands as the foremost cause of mortality within the nation of Iraq, exhibiting a prevalence rate of 9.24% per 100,000 individuals. The transmission of primary tuberculosis (TB) [6] can occur through the inhalation of airborne infected droplets or through direct contact with individuals who are infected and exhibit symptoms such as coughing or sneezing. In the year 2015, a striking 10.4 million fresh cases of tuberculosis infections emerged globally, and this ailment was responsible for the unfortunate demise of 1.8 million individuals. It is noteworthy that a significant proportion of tuberculosis-related fatalities [6] are concentrated in countries that are categorized as developing nations. Despite this, it is depressing to learn that the ambitious goal outlined by the End TB Strategy for the year 2020 will not be accomplished, with predictions indicating that a staggering 10 million people will have succumbed to TB by that time.

Within the borders of Iraq, a populace of 56 hundred thousand adult males, 33 hundred thousand adult females, and 11 hundred thousand children coexist, representing diverse demographics vulnerable to the pervasive threat of tuberculosis. Importantly, tuberculosis is a malady that exhibits the capacity to afflict individuals across all strata of race, gender, and age.

On the other hand, tuberculosis is treatable and can be avoided entirely [5, 6]. Without a doubt, this is a matter of public health continues to present a significant obstacle for the healthcare systems of nations, particularly in developing countries. Since the 1980s, medical image analysis and processing methods have come a long way [4], which provides an informative overview of these developments. Image classification refers to the process of determining various categories that exist within a single photograph. You have the option of using supervised methods or unsupervised methods when it comes to classification work. In unsupervised classification, we start with a set of available classes and characterize them by measuring the variables in people whose membership in one of the classes is certain, we can categorize people according to the set of variables. On the other hand, in supervised classification, we start with a set of available classes and characterize them based on the combination of factors that are measured in individuals who are confident that they belong to one of the classes. In this study, artificial intelligence was utilized to automatically categorize X-ray chest images as positive or negative for tuberculosis.

In the corresponding sections, Section 2 provides an overview of the techniques and findings that have been utilized by different researchers to prediction of tuberculosis, Section 3 includes the current methodologies, their benefits and drawbacks, and Section 4 offers a conclusion.

2. Methodology:

In this research article, researchers use popular deep learning methodologies used for the detection of Tuberculosis diseases. This article’s primary goal is to analyze the commonly used deep learning methodologies for the detection of tuberculosis.

2.1. Research Objectives:

This study aims to achieve the following primary goals:

1. Compare and contrast the usefulness of the various TB classification schemes.
2. Provide an overview of the current and prospective research efforts that are taking advantage of the benefits of tuberculosis disorder categorization.
3. Depending on the TB disease's classification, identify the most recent research trends and publication interests. The following table details the selection and rejection criteria for the study.

2.2. Search String:

(Searches containing the terms "tuberculosis," " tuberculosis chest x-ray," " tuberculosis classification," "tuberculosis synthetic intelligence," OR " tuberculosis computer-aided diagnosis" OR "Tuberculosis disease Prediction" OR " tuberculosis Deduction" OR "Tuberculosis Deduction" OR "Deep learning on tuberculosis " OR " tuberculosis DL"OR " tuberculosis Neural network" OR " tuberculosis NN" OR " tuberculosis ML" OR " tuberculosis Convolution" OR " tuberculosis Radiograph")

OR

("Tb," OR "chest x-ray," OR "Tb classification," OR "Tb synthetic intelligence," OR "Tb computer-aided diagnosis" OR "Tb disease Prediction" OR "Tb Deduction" OR " OR "Deep learning on Tb" OR "Tb DL"OR "Tb Neural network" OR "TB NN" OR "Tb ML" OR "Tb Convolution" OR "Tb Radiograph")

Elsevier, ACM, Google Scholar, IEEE Digital Library, Springer, Nature Scientific Reports, Science Direct, and Web of Science are among the most dependable and trustworthy digital data sources to use while looking for the precise publications that are needed for a research inquiry. To find pertinent articles from all data repositories, two main search phrases are used.

2.3. Selection Criteria:

Table 1: Eligibility criteria

INCLUDE	EXCLUDE
Articles presenting good foundation knowledge for tuberculosis classification	Articles that are not limited to tuberculosis classification
Articles that used publicly available X-ray dataset	Articles whose datasets are not publicly available as open source
Articles that are written in the English language	Articles that are not available in the English language
Articles that are presenting technical solutions using deep neural networks for tuberculosis detection	Articles that only discussed tuberculosis but not focused on deep learning/machine learning-based solutions
	Articles that are published before January 2010

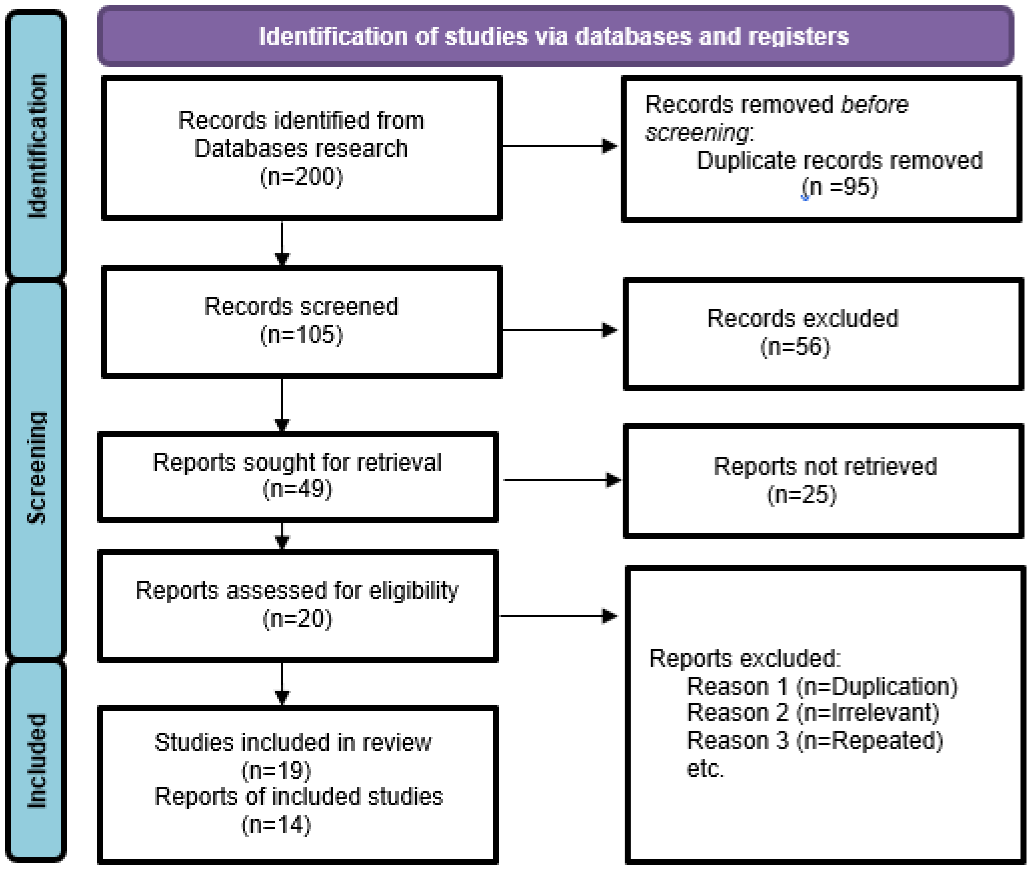

Figure 1: Identification of Studies

3. Deep Learning Methodologies:

In recent past years, the field of deep learning has yielded numerous exemplary solutions to Computer-Aided Design (CAD) problems. Notably, deep learning has swiftly become the standard practice within the realm of radiology [24]. Deep Convolutional Neural Networks (DCNNs), principally through feature extraction, have shown to be essential tools for the prediction of tuberculosis (TB) patients and Classifying chest X-Ray images into either normal or abnormal categories.

The core components constituting the CNN architecture encompass the convolutional layers, pooling layers, and fully connected layers (FC). Convolutional layers are responsible for the extraction of pertinent information from images via convolution operations. Subsequently, pooling layers, often situated after convolution layers, serve the purpose of reducing the dimensionality of feature maps. Maximal and average pooling represent the two prevalent types of pooling operations: the former selects the most significant element within a window (typically 2X2), while the latter computes the average of all components. The pooling layer serves a crucial function in addressing overfitting, thereby decreasing the computational workload and the quantity of network parameters. The fully connected (FC) layers are responsible for encoding all the input image information and are specifically tailored to classify the input image by utilizing the features gathered in the earlier layers. After the FC layer, further processing is done using activation techniques like SoftMax. With more than 15 million high-resolution photos divided into roughly 22,000 groups, ImageNet is a renowned visual collection. Using the ImageNet dataset, researchers frequently evaluate the effectiveness of their picture classification methods. To gauge the efficacy of deep learning techniques in the 2012 ImageNet challenge, the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) employs a subset of ImageNet containing only 1000 categories. Recent years have witnessed a resurgence of interest in CNNs, fueled by the development of novel network architectures and cutting-edge Graphics Processing Units (GPUs). Contemporary computational resources enable the training of increasingly intricate convolutional networks [31].

In addition to seminal CNN architectures like LeNet [25], AlexNet [26], VGGNet [27], GoogleNet [28], ResNet [29], DenseNet [30], and R-CNN [36], numerous CNN variants have been proposed. A common framework for TB classification incorporates convolutional layers, sub-sampling/pooling layers, and fully connected layers, akin to the LeNet neural network model. AlexNet, as detailed by Krizhevsky et al. [26], is a deep convolutional neural network characterized by five convolutional layers and three fully connected layers. It introduced the ReLU activation function in place of the sigmoid activation function to expedite model training. VGG-16 [27], devised by K. Simonyan and A. Zisserman,The Visual Geometric Group (VGG) research team has devised a series of convolutional network models that incorporate a total of 13 convolutional layers along with three fully-connected layers. This sequence of models initiated with VGG-11 and extends to encompass VGG-13, VGG-16, and VGG-19. Their primary focus is the investigation of how the depth of a convolutional network influences the reliability of image recognition and classification algorithms. VGG architectures vary in depth, featuring eight, sixteen, or nineteen fully linked convolutional layers, with the final three fully connected layers remaining consistent across all VGG variations. GoogleNet introduced a 22-layer image classification network that utilizes the concept of inception layers, which convolve input layers in parallel with varying filter widths. ResNet, proposed by Kaiming He et al. [29], boasts 33 convolutional layers and one fully-connected layer. While earlier models incorporated deep neural networks with multiple hidden layers, they encountered challenges related to vanishing or exploding gradients. To tackle the vanishing gradients problem, skip layers, or shortcut connections, were introduced. Gao et al. developed DenseNet [30], which features both dense blocks and transition blocks. Within the thick block, after the third batch normalization layer, a ReLU activation and a three-by-three convolution operation are executed. Transitional blocks are composed of essential components including batch normalization, 1x1 convolutions, and average pooling. When contrasted with conventional manually designed feature detectors, Convolutional Neural Networks (CNNs) present a highly effective method for feature extraction in the context of object recognition, resulting in remarkable classification performance. However, there is still a big need for sufficient data to train CNNs and reduce overfitting. In the medical field, the challenge of data scarcity can be addressed through transfer learning. Pre-trained CNN models serve as feature extractors, followed by refinement with domain-specific data using one of two transfer learning strategies.

Many excellent CAD problem solutions have emerged from the rapidly developing subject of deep learning in recent years. Deep understanding has quickly become the standard practice in radiology [24]. Deep Convolutional Neural Networks (CNNs) have demonstrated their essential role in the identification of tuberculosis (TB) cases and the classification of chest X-ray images as either normal or abnormal by effectively extracting relevant features. The main layers that comprise the CNN architecture are the convolutional, pooling, and fully connected layers (FC). Using a convolution operation, information from an image is extracted using convolutional layers. The pooling layer typically comes after the convolution layer to help reduce the feature map's dimensionality. The two most popular kinds of pooling operations are maximal and average pooling. In maximum pooling, in max pooling, the most crucial feature within a 2x2 window is chosen, whereas in average pooling, the mean value of all elements within the window is calculated. The pooling layer serves the additional purpose of preventing overfitting, leading to a reduction in both computational load and the number of network parameters. All of the image input data is encoded using FC layers. The purpose of the FC layer is to classify the input image based on the features learned in the preceding layers. Activation methods such as SoftMax are used for further processing after the FC layer.

ImageNet is an excellent visual data set with over 15 million high-resolution images classified into roughly 22,000 categories. Researchers routinely put their image classification systems through their paces on the ImageNet dataset. To determine how well deep learning techniques perform on the 2012 ImageNet challenge, the ILSVRC uses a subset of the ImageNet, including only 1000 categories. The development of new kinds of networks and cutting-edge graphics processing units (GPUs) have stoked a resurgent interest in CNNs in recent years. Thanks to modern computational resources, more profound and more complex convolutional networks may be trained [31]. Numerous CNN variations have been proposed in addition to LeNet [25], AlexNet [26], VGGNet [27], GoogleNet [28], ResNet [29], DenseNet [30], and R-CNN. [36] A CNN framework based on the LeNet neural network model for TB classification.Common architectural components include convolutional layers, pooling or sub-sampling layers, and fully connected layers.. The deep convolutional neural network AlexNet consists of five convolutional layers and three thoroughly combined layers, as stated by Krizhevsky et al. [26]. AlexNet replaced the sigmoid activation function with the ReLU activation function to speed up model training. K. Simonyan and A. Zisserman developed VGG-16 [27], which features 13 convolutional and three fully-connected layers. The Visual Geometric Group (VGG) team of researchers developed a family of convolution network models beginning with VGG-11, VGG-13, VGG-16, and VGG-19. The VGG team's primary focus is on learning how the depth of a convolutional network affects the reliability of image recognition and classification algorithms. Between the minimum VGG11 and the highest VGG19, there are eight, sixteen, and three wholly linked convolutional layers. For all VGG variations, the last three fully connected layers are the same. This view is shared by Szegedy and others [28]. A 22-layer image classification network called GoogleNet was proposed. GoogleNet's fundamental idea is to add layers of thought to an existing framework. Each inception layer convolves its input layers in parallel using a different filter width. ResNet was proposed by Kaiming He et al. [29], and it has 33 convolutional layers and one fully-connected layer. Several models were ahead of the curve by utilizing intense neural networks with several hidden layers. However, it was later shown that these models suffered from issues with vanishing or exploding gradients. The concept of skip layers (shortcut connections) is introduced to solve the vanishing gradients issue. There are both dense blocks and transition blocks in the system developed by Gao et al. for their DenseNet [30]. After the third batch normalizing layer, the thick block performs a ReLU and a three-by-three convolution operation. Transitional blocks utilize techniques such as batch normalization, 1x1 convolutions, and average pooling. When contrasted with state-of-the-art manually designed feature detectors, Convolutional Neural Networks (CNNs) stand out as an efficient approach for feature extraction in objects and consistently deliver strong classification performance. The amount of data needed to train CNN and prevent overfitting was tremendous. Transfer learning could solve the problem of a need for more comprehensive data in the medical profession. As a feature extractor, we use a pre-trained CNN model; after that, we employ one of two transfer learning strategies: I am refining a pre-trained CNN model with data from the relevant area.

As seen in [6], one frequent image processing use is isolating target areas. Computer-assisted diagnosis software examines the images, separates the textures, and pinpoints the region of interest. A Parkinson's disease diagnosis may be linked to these traits. We learnt how to find micro calcification clusters in digital mammography pictures using AI, pattern recognition, and image processing in [7]. The inability to easily compare and replicate novel methodologies was exacerbated by the fact that only a tiny fraction of studies [8, 9] tapped into publicly available databases. After applying computer vision algorithms to a combined free and open database of radiography images, researchers presented their findings as the first segmentation of the lung region [9]. Although it adopts a different strategy from this one, it still encourages the use of freely accessible resources for model testing and training. Most studies on multilayer perceptron neural networks for tuberculosis identification ignored the possibility of using medical images as inputs to the ANNs. They reasoned that ANN training could benefit from data collected during routine medical office visits, such as patient temperatures, coughs, and breathing issues. Various amylase, cholesterol, blood pressure levels, and other laboratory data. These studies show that ANNs can be used to diagnose TB using real-world data. However, this process still necessitates medical testing and the participation of qualified specialists, which are only sometimes feasible or available, in particular considering the average TB patient profile. This study proposes a method that employs only radiographic images of the lungs, a low-cost, easily accessible test that overcomes these disadvantages and is more applicable to real-world settings. Some relevant articles [8-10] provide a synthesis of techniques for improving medical images; these can be used [11] to eliminate noise from the image using erosion, extraction, and other methods often used in the state-of-the-art. Like [12-15], [9] is another image-processing study that uses the technique to aid in the early diagnosis of breast cancer. One can see that texture-based segmentation was employed in this work, using evidence images drawn from a library of pathology images annotated by humans to identify malignant masses and micro calcifications. Digital image processing and texture analysis are used to find and extract all the regions of interest in thermal images to detect breast cancer [16-18].

3.1. Datasets:

Data is essential for developing the CAD needed to combat high-mortality diseases like tuberculosis (TB). To ensure patient anonymity, de-identified CXR pictures are among the many publicly available resources used to train TB detection algorithms. The patients' identities, in other words, are kept secret. A radiological interpretation of the observed symptom is commonly included in the datasets and can be relied upon as an authoritative source. By making this data available to the research community, we aim to spur innovative exploration of long-term solutions for early diagnosis of TB symptoms. The Montgomery County [19], Shenzhen [19], Peruvian [23], KIT [20], MIMIC-CXR [21], Belarus, NIH (chest x-ray 8, 14) [22], JSRT (India), IN, and Belarus databases are all examples of publicly available datasets.

4. Literature Review:

To achieve this objective, we conducted a comprehensive literature review and synthesized studies published on the application of Convolutional Neural Networks (CNNs) for tuberculosis (TB) diagnosis from chest X-ray (CXR) images during the period spanning from 2010 to 2020. CNNs have garnered significant attention due to their exceptional pattern recognition capabilities, making them a pivotal component in the development of Computer-Aided Diagnosis (CAD) systems. Compared to conventional statistical approaches, CNN models have shown to perform better in the field of outcome prediction.

Liu et al. [32] undertook the task of training updated iterations of the AlexNet and GoogleNet CNN models for the detection of TB symptoms in X-ray images, achieving an impressive accuracy rate of 85.68 percent. Hooda et al. [33] contributed to this area by presenting a trio of architectures, namely GoogleNet, AlexNet, and ResNet, for TB detection. The overall correctness of the ensemble architecture was 88.24%.

Hwang et al. [35] ventured into TB diagnosis using deep convolutional neural networks (CNNs) by adapting the AlexNet architecture and integrating transfer learning into their approach. In a similar vein, this study presents a TB detection methodology employing a 14-layer convolutional neural network (CNN) architecture alongside a data augmentation strategy. Using chest X-ray (CXR) images sourced from publicly available datasets like MC, CH, and IN, this convolutional neural network (CNN) model showcases an impressive accuracy of 87.29%.

Ghorakavi [38] put forth an approach that leveraged a deep neural network, specifically ResNet18, strengthened by the implementation of data augmentation techniques, which led to notable improvements in performance. In a related vein, S. J. Heo et al. [39] developed the D-CNN framework, which smoothly integrates Image CNN (I-CNN) with other demographic characteristics such as age, height, weight, and gender, hence broadening the scope of their research. When compared to I-CNN, D-CNNs demonstrate the capacity to identify tuberculosis from chest X-rays, with demographic factors enhancing diagnostic precision.

T Karnkawinpong and Y Limpiyakorn [48] examines the classification of tuberculosis in chest X-ray images using AlexNet, VGG-16, and CapsNet. Customized models are built with datasets from the National Library of Medicine and Thai sources, incorporating data augmentation to prevent overfitting. The research assesses the effectiveness of the classifier, demonstrating improved accuracy with enhanced datasets, and investigates the effect of affine transformation on variant instance prediction in the test set.

Islam et all. [49] investigates DCNN-based abnormality detection in frontal chest X-rays, addressing the inadequacies in existing literature due to private datasets or insufficient reporting of test scores. Utilizing the publicly available Indiana chest X-ray dataset, the study evaluates various DCN architectures' performance across different abnormalities, revealing varying efficacy. Notably, ensemble models outperform single DCNN models, while combining DCNN with rule-based models diminishes accuracy.

The paper achieves the highest accuracy in chest X-ray abnormality detection, with a notable 17% improvement in cardiomegaly classification. The study also highlights successful localization of spatially spread abnormalities but notes challenges with pointed features, providing valuable insights for future exploration.

Lakhani and Sundaram [40] put forth a fusion approach, combining the architectural attributes of GoogleNet and AlexNet for TB detection. Nguyen et al. [41] underscored the significance of utilizing appropriate pre-training data, as they found that the weights derived from ImageNet were inadequate for TB detection via transfer learning.On the other hand, in their study, Sivaramakrishnan and colleagues [42] performed a comparative evaluation of five pre-trained Deep Learning (DL) models for the detection of tuberculosis (TB) in chest X-rays (CXRs). Their findings indicated that pre-trained deep learning models consistently exhibited superior performance compared to custom-built models.

Furthermore, commercial software solutions have been developed to facilitate TB detection, including CAD4TB. Researchers in [43] evaluated the diagnostic accuracy of CAD4TB software in detecting pulmonary TB (PTB) against a microbiological reference test, yielding an area under the curve (AUC) ranging from 0.71 to 0.84, attributable to the high sensitivity of the CAD4TBv6 program.

An in-depth analysis and comparison of three state-of-the-art Deep Learning systems, specifically qXR, CAD4TB, and Lunit INSIGHT, will be conducted. This was conducted by the authors of [44] to detect TB-related anomalies in CXR images. In their investigation, which entailed a thorough evaluation of each DL system's performance, it was discovered that CAD4TB, qXR, and Lunit outperformed human specialists in distinguishing between instances of tuberculosis and those that weren't.

Table 2, which includes important performance parameters accuracy, presents a comparative overview of CAD systems that use deep learning approaches for TB classification in CXR pictures.

Table 2: Results

Ref.	Data set (CXR Images)	Classifier	Accuracy
[40]	1007 MC, CH, TJH, Belarus	AlexNet TA & GoogLeNet TA	96 %
[48]	3310	AlexNet	92.9 %
		VGG 16	94.56 %
		CapsNet	90.33 %
[44]	TBX11K	CNN	89.7 %
[43]	1133	Ensemble of (AlexNet, GoogleNet &ResNet)	88.24 %
[36]	MC, CH, IN (1078)	CNN	87.29 %
[42]	4701	CNN	85.68 %
[49]	CH	ALEX NET	84 %
		VGG 16	84 %
		VGG 19	80 %
		RESNET 50	86 %

		RESNET 101	84 %
		RESNET 152	88 %
		ENSEMBLE	90 %
[46]		CNN (7Conv, 7ReLu, 3FC and 2dropouts layers)	82.3%
[38]	800	Deep ConvNet	58.35 %
		Resnet 18	65.77 %
[47]	60989 SNUH, BMC, KUHG DEMC, MC, CH	DLAD	97 %
[35]	10848 KIT, MC, CH	AlexNet with transfer learning	90 %
		AlexNet without transfer learning	71 %
[34]	CH, MC, Kenya, India	AlexNet,	85.3 %
		VGG 16	85.5 %
		VGG 19,	85.2 %
		Xception	81.5 %
		ResNet 50	80.2 %
[50]	MC, CH	Modified AlexaNet Modified VGGNet	N/A
[41]	MC, CH	Transfer learning models for different initialized weights	N/A
[39]	1000 YU, AWH	DCNN (Image CNN + Demographic variable)	N/A

CAD systems are critical for boosting the precision of CXRs in low-income, rural areas for tuberculosis detection. According to our research, a deep learning-based CAD system is necessary for accurate TB detection from CXR pictures. The automatic feature extraction methodology that deep learning uses is its main advantage over other methods. A technology that could be useful for TB identification in CAD systems is a network of convolutional neural networks (CNNs).

5. Conclusion & Future scope:

This publication serves as a concise guide for emerging researchers keen on delving into the exploration of deep learning methodologies applied in the diagnosis of Tuberculosis (TB) through Chest X-ray (CXR) images. It summarizes essential aspects of this research. The overarching objective of Computer-Aided Diagnosis (CAD) systems is to detect and diagnose TB through a meticulous examination of CXR images. While there has been acceptance of CAD systems for TB detection by the World Health Organization (WHO), further substantiation is imperative for full endorsement. This paper conducts a systematic evaluation of TB detection methods, shedding light on the exigency for additional research in CAD systems utilizing CXR for TB detection. The WHO's approval of CAD systems is a big step, but the need for further proof shows how conservative this technology is in TB diagnosis. The systematic review performed herein accentuates the critical need for continued exploration and refinement of CAD systems relying on deep learning for TB diagnosis. Therefore, we can conclude that AI-based CAD systems will be crucial for TB detection [42].

Looking forward, the landscape of deep learning-based CAD for TB diagnosis unfolds a multitude of promising research prospects. In the future, researchers could look into ways to make the models easier to understand and explain, how to make them work best for a wide range of populations, and what ethical issues might come up when using this kind of technology in clinical settings. Also, looking into how to combine different types of data and make real-time diagnostics better could make deep learning-based CAD even more useful for diagnosing TB. This continuous investigation helps to improve diagnostic techniques and opens the door for the development of more practical and affordable healthcare solutions.

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