Primary Diagnosis of Pulmonary Tuberculosis using AI Based Expert Systems: A Review

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Abstract: Tuberculosis (TB) is a very contagious infectious airborne sickness that has caused more deaths than any other disease. Despite being discovered over a century ago, it remains a global health threat, with high mortality rates due to delayed or missed diagnosis. TB is preventable and curable, but early detection is crucial to prevent transmission and improve treatment outcomes. Traditional methods of diagnosis, such as bacteriological tests and chest X-rays, can be time-consuming and prone to errors. Therefore, there is a need to develop accurate and efficient tools to detect TB at an early stage. Deep learning is a cutting-edge technique in the field of artificial intelligence that has the potential to be incorporated into computerized diagnosis systems for the purpose of performing automated TB detection in chest X-rays. The ultimate goal is to reduce patient waiting times and improve TB control. This article explores the challenges and opportunities involved in using deep learning for computer-generated diagnoses of active pulmonary tuberculosis in chest X-rays.

Keywords: Tuberculosis, Artificial Intelligence, Deep Learning

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I.INTRODUCTION

There will be roughly ten million persons diagnosed with tuberculosis (TB) in the year 2020, according to the World Health Organization (WHO). This includes 5.6 million men, 3.3 million women, and 1.1 million children. During the same year, tuberculosis was a reason of death for 1.5 million individuals all over the world, including 214,000 persons living with HIV. India is one of the nations that will have the largest prevalence of tuberculosis in 2020 due to the fact that it affects two thirds of its population [1].

The pathogen known as Mycobacterium tuberculosis is the agent that is responsible for the development of tuberculosis, more often referred to as TB. The infectious potential of tuberculosis is quite great. When an infected individual coughs or sneezes, tiny particles in the air may get dispersed into the surrounding environment and cause the sickness to spread from one person to another. Pulmonary tuberculosis (PTB) is the type of tuberculosis that predominantly affects the lungs, while extra-pulmonary tuberculosis (EPTB) is the form of tuberculosis that mostly affects other parts of the body. Both forms of tuberculosis are contagious and may be fatal (EPTB)[2].Diagnosing TB can be a challenging task because the signs of active PTB can vary and may present at different stages of the disease. These symptoms may begin with a mild or progressing dry cough, which may initially be symptom-free, and then develop to more severe fever, exhaustion, diminished appetite, sweating at night, and a cough with bloody phlegm [3].

There are several ways to confirm tuberculosis (TB), including GeneXpert assay, sputum-smear microscopy, and Chest X-Ray (CXR). However, the traditional methods of diagnosing TB can be time-consuming, which can lead to delays in treatment and potentially result in drug resistance, including Multi-Drug Resistance (MDR) and Extensive-Drug Resistance (XDR). [4].Despite the fact that TB can be effectively treated with antibiotics, its mortality rate remains high, largely due to cases being either undetected or detected at an advanced stage. Early diagnosis is crucial to effectively eradicating TB and minimizing mortality rates associated with the disease. [5].Radiographic imaging, particularly Chest X-Ray (CXR), may be very helpful in making an accurate identification of tuberculosis (TB) when bacterial tests are unable to provide a satisfactory answer. The World Health Organization (WHO) recognizes CXR as an important tool for TB screening, which is not only effective but also cost-efficient. [6].Diagnosing TB through chest X-rays is a time-consuming process that requires skilled personnel, which is not feasible in countries with high rates of TB and limited resources [7]. As a result of this, there has been a little curiosity in the application of computer-aided diagnostics for the determination of PTB using CXR.

Over the course of the past few years, the fast growth of information technology has led to a growing interest in Artificial Intelligence among experts working in the medical field (AI). When it comes to the evaluation, therapy, and general well-being of patients, the development of AI-powered systems and the implementation of such systems in medical practice are becoming increasingly crucial. [8]. Deep Learning (DL), a subset of Artificial Intelligence (AI), employs many levels of processing to automatically detect and extract complex features that are essential for differentiating patterns from huge datasets [9]. Presently, deep learning methods are regarded as the most advanced techniques for image classification. Therefore, there is growing interest in using deep learning to analyze radiological findings due to its recent achievements and promising outcomes. [10]. In recent years, supervised machine learning algorithms such as convolutional neural networks (CNNs) have gained popularity as a valuable tool for tuberculosis (TB) monitoring and screening. CNNs are built from several layers of convolutional processing, as well as layers of pooling and fully-connected processing. These models make use of big datasets with the goal obtain variables and derive global and local characteristics from an image that are extremely discriminative. In addition to this, CNN models do not need any domain-specific expertise for it to function and are capable of representing features in an effective manner [5]. The increased interest in CNNs recently can be ascribed to the development of new network varieties and the availability of modern GPUs. Several types of CNNs have been introduced, including LeNet, AlexNet, VGGNet, GoogleNet, ResNet, DenseNet, and R-CNN. The AlexNet CNN model was the first to be utilized for TB classification in CXR.[6].This paper provides a brief review of research papers on TB detection using deep learning models with CXR images. Furthermore, the paper highlights the challenges encountered in this field and suggests future research trends.

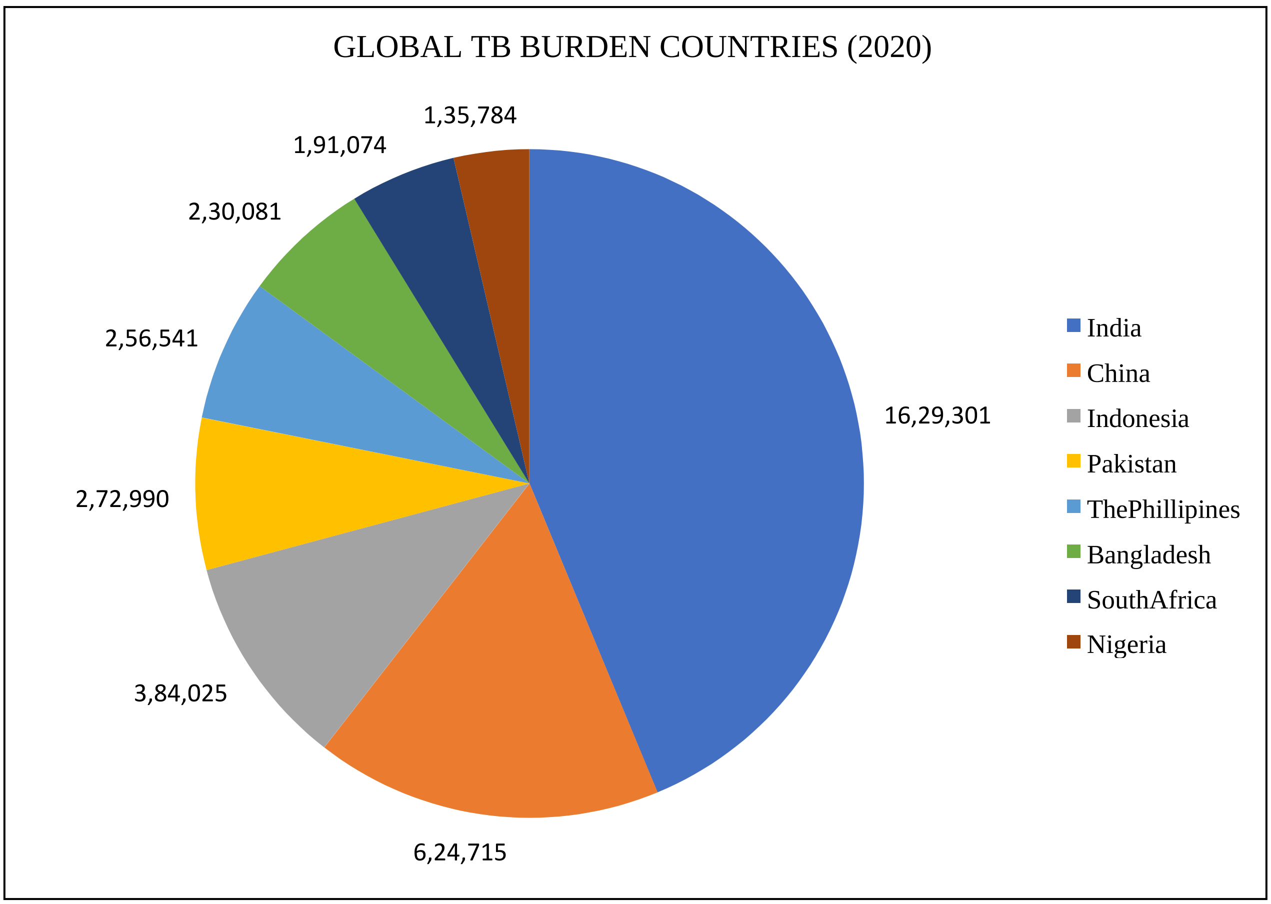

Fig1: Global TB burden countries as of 2020 report [30]

II. LITERATURE REVIEW

The application of deep learning and artificial intelligence frameworks for identifying and making a diagnosis of pulmonary tuberculosis (TB) from chest X-ray (CXR) pictures is the overarching theme that is covered in the research articles that are going to be summarized. The papers review and compare different CNN-based models and their performance in TB detection, using various techniques such as transfer learning, ROI localization, pre-processing, feature selection, and ensemble models. The papers also explore the potential of AI-based expert systems for TB screening, including the discrimination between drug-sensitive and drug-resistant TB, and the use of shape and texture characteristics for classification. Overall, the papers aim to develop efficient, accurate, and automated systems for TB diagnosis, which can aid healthcare professionals in the early identification and treatment of the disease.

Hwang et al., were the pioneers who proposed utilizing a deep convolutional neural network (DCNN) for the purpose of detecting TB in chest X-rays. They accomplished this by utilizing a customized version of the Alex Net network and a method known as transfer learning, which resulted in an accuracy rate of 90%.

Santosh et al., was motivated by the finding that a TB-infected chest x-ray may exhibit distorted thoracic edge maps during automated pulmonary abnormality assessment. They did this by applying five different ROI localization approaches so as to select the model that performed the best altogether.

Cao et al., set out to create an extensive and properly labeled database of X-ray images for tuberculosis (TB) screening, while also focusing on developing efficient convolutional neural network (CNN) frameworks for the classification of photos into the many types of TB symptoms. They were able to attain an accuracy of 89.6% through binary classification after a certain number of iterations without utilizing any pre-processing methods.

In their prospective study, **Lakhani and Sundaram** deployed two different deep convolutional neural networks (DCNNs), namely AlexNet and GoogleNet, to categorize X-ray pictures as either having pulmonary tuberculosis (TB) symptoms or as being healthy. They augmented the dataset by using untrained as well as preconditioned networks from ImageNet and various different preprocessing approaches. In addition to this, they utilized ensembles of the algorithms that performed the best in order to further improve the system's overall performance. The findings of this study exceeded the findings of the research conducted by Hwang and colleagues, which exhibited area under the curve (AUC) values in the range of 0.88 to 0.96.

Lopes and Valiati introduced a transfer learning technique that involved using previously trained model weights with some tweaking on the last layers by implementing GoogleNet, ResNet, and VggNet in their study. They presented three proposals, which were executed and compared to existing literature to showcase the capabilities of pre-trained convolutional neural networks (CNNs).

Hooda et al., used CNN architecture with 7 convolutional layers and three layers that were completely linked to classify CXR images as normal and abnormal. The outcomes of three other optimizers was then examined, and it was determined that the Adam optimizer produced the most accurate results.

Islam et al., explored various DCNN models comprising of AlexNet, VGG-16, VGG-19, ResNet-50, ResNet-101, ResNet-152 for chest X-Ray abnormality detection. They discovered that the same DCN design fails to execute effectively with all types of anomalies, although shallower elements frequently provide greater accuracy in detection in comparison to deep features. In addition to this, they discovered that using ensemble models greatly improved categorization compared to using only one model.

Rohilla et al., employed convolutional neural network (CNN) models to categorize chest radiographs as either TB positive or TB negative, and evaluated the performance of the system on two datasets - MC and SH. They utilized modified versions of AlexNet and VGGNet on both datasets, with the modified VGGNet outperforming the modified AlexNet, as well as the original versions of both models. The modified VGGNet achieved an accuracy of 81.6%.

Haloi et al., introduced an automated artificial intelligence aided screening (AIAS) system, which is an extremely profound fully convolutional classification network that also makes use of online augment. This method achieves state-of-the-art performance on accessible databases, in addition to generating confidence ratings for the illness prevalence.

Jaeger et al., sought to create a tool for distinguishing between drug-sensitive and drug-resistant tuberculosis by utilizing an artificial neural network in conjunction with a group of shape and texture features. They were able to attain an area under the curve (AUC) of up to 66%, which denotes the probability of a drug-resistant tuberculosis infection that can be detected computationally in chest X-rays.

Santosh et al., investigated the symmetrical properties of the lung area using multi-scale shape characteristics as well as edge plus texture features. The shape characteristics capture both the regional and global representations of lung regions, whereas the edge and texture characteristics consider internal content, including the physical arrangement of the structures. For the goal of classification, the authors made use of Bayesian networks, multilayer perceptron neural networks, and random forest models.

Vajda et al., developed a method for determining if CXRs are healthy or unhealthy by employing lung segmentation, choice of features, and neural network classification in tandem with one another. They began by employing an atlas-based segmentation technique to segment the lung area, and after that, they retrieved an extensive collection of conventional picture characteristics. They trained a neural network classifier utilizing the selected features after applying a wrapper-type feature selection technique to choose the best feature set for classification. On a dataset consisting of 500 CXRs, the performance of their technique was examined, and the results showed that it attained a precision of 87.4%.

Sivaramakrishnan et al., compared five pre-trained deep learning models (VGG16, InceptionV3, InceptionResNetV2, ResNet50, and Xception) with a customized model for tuberculosis detection from CXRs. In terms of precision, specificity, and sensitivity, they discovered that the pre-trained deep learning models performed significantly better than the individualized model.

Hwang et al., have created an algorithm called deep learning based automatic detection (DLAD), which consists of 27 layers and 12 residual connections, using deep learning techniques. The accuracy of the algorithm was evaluated using six different external datasets. The results showed that DLAD was more effective than physicians, including radiologists, in detecting active pulmonary tuberculosis through chest x-rays.

Meraj et al., investigated whether or not it would be possible to provide an effective diagnosis of tuberculosis (TB) in chest x-rays (CXRs) by using simple convolutional neural network models, in spite of the restricted processing capacity and compact model design. They used the VGG-16, VGG-19, ResNet50, and GoogleNet models as their foundational tools. As compared to the models that were used in the two earlier experiments, their results demonstrated that the VGG-16 model had the greatest overall accuracy score.

Using a convolutional neural network, **Pasa et al.,** developed a straightforward and effective deep learning model for spotting tuberculosis (TB) in chest radiographs. The algorithm uses deep learning techniques. After a series of average pooling layers and a softmax layer comes a series of five convolutional layers that make up the model. The accuracy of the model, when tested on a pooled dataset, was determined to be 86.2% having been trained from scratch using solely chest radiographs. The authors emphasise that the straightforwardness of the approach is one of its most appealing qualities.

Hooda et al., .recommended using a combination of three different deep learning architectures to classify tuberculosis (TB) in chest images. These architectures were named AlexNet, GoogleNet, and ResNet. The model was trained and tested using pooled datasets that were made accessible to the public, and it outperformed other approaches in terms of being precise.

Heo et al., suggested a deep convolutional neural network (CNN) for detecting tuberculosis (TB) in chest radiographs. Their model, called D-CNN, consists of both an Image CNN and demographic features such as age, height, weight, and gender. In their study, they found that the D-CNN model had higher accuracy than the Image CNN alone.

Kyung et al., evaluated the possibility of improving the accuracy of a deep learning model for diagnosing tuberculosis (TB) using chest X-rays (CXR) by applying a two-stage semi-supervised technique that makes use of unlabeled datasets. This study was carried out in order to investigate the possibility of improving the accuracy of the model. According to the findings, the model was successful in detecting tuberculosis (TB) with a high degree of precision and showed promise as a useful computer-aided detection (CAD) instrument.

Liu et al., have created a TB dataset named TBX11K, which comprises 11,200 CXR images that are annotated with bounding boxes to indicate TB regions. They have also developed a computer-aided tuberculosis diagnosis (CTD) system using deep learning techniques.

A research was carried out by **Ayaz** in which they attempted to diagnose tuberculosis (TB) by analysing chest X-ray (CXR) pictures using a number of different pre-trained convolutional neural network (CNN) models using supervised learning. The research was conducted in three stages. Secondly, they investigated how well various CNN architectures performed as feature extractors and compared their results. In the second step of the process, they investigated the use of the Gabor filter as a feature extractor. Their tuberculosis (TB) prediction model achieved a very high degree of accuracy as a consequence of the last step, which was the application of ensemble learning to the combination of the separate results obtained during the first twostages.

TABLE I
REVIEW OF DEEP LEARNING BASED CADSYSTEMS

Author	Year	Dataset	Method	Accuracy(%)	AUC (Area Under the Curve)	Purpose
Hwang et al.,	2016	Private Dataset, MC and SH Datasets	CNN (Modified AlexNet)	90.00	0.964	To develop a novel approach based on Deep CNN for TB screening to gain better accuracy for effective TB detection
Santosh et al.,	2016	MC and SH Datasets	NN	79.23(MC) 86.36(SH)	0.88(MC) 0.93(SH)	Using distorted thoracic edge maps as the foundation for a tuberculosis screening method. system based on deformed thoracic edge maps.
Cao et al.,	2016	4701 Images from partners in Health at Peru	DCNN (GoogleNet)	89.6(binary classification) 62.07(multi class classification)	-----	Using distorted thoracic edge maps as the foundation for a tuberculosis screening method.
Lakhani and Sundaram	2017	MC, SH,TJH, Belarus	Supervised DCNN Ensemble(AlexNet, GoogleNet,)	96(ensemble)	0.99(ensemble)	The primary goal of this study is to investigate how well DCNN works for spotting TB on chest radiographs.
Lopes and Valiati	2017	MC and SH Datasets	CNN Ensemble(GoogleNet, ResNet and VggNet)	82.6(MC) 84.7(SH)	0.926(MC) 0.926(SH)	In order to offer a transfer learning strategy, pre-trained model weights were used, and the final layers saw some fine tuning.
Hooda et al.,	2017	---	CNN (7conv,7ReLu,3FC and2dropouts layers)	94.73(Overall)82.09(validation)	------	In order to create a potentially useful approach for the identification of TB utilizing CXR
Islam et al.,	2017	Inadiana, JSRT and SH datasets	DCNN Ensemble(Alex Net, VGG-16,VGG-19,ResNet-50,ResNet-101,ResNet-152)	93(Ensemble)	------	To detect the abnormality and perform localization in CXRs
Rohilla et al.,	2017	MC and SH datasets	CNN (Modified Alex Net and modified VGG Net)	80.4(modified AlexNet) 81.6(modified VGGNet)	-----	To test deep learning methods on detection of TB in CXRs
Haloi et al.,	2018	ChestXray-14, Mendeley, MC, SH and Belarus	DCN N(AI AS)	-----	0.949	The goal of this project is to construct a completely automated system that is capable of recognizing disease features without any offline preprocessing or human feature extraction.
Jaeger et al.,	2018	Belarus	ANNC NNVG G-16	ANN Experiment1:60 Experiment2:62	ANN Experiment1:0.65 Experiment2:0.66	In order to distinguish between drug-sensitive and drug-resistant forms of tuberculosis in CXR
Santhosh et al.,	2018	MC, SH and IN dataset	Bayesian network, Neural network, Random Forest	83(MC) 86(IN) 91(SH)	0.90(MC) 0.94(IN) 0.96(SH)	To determine if a CXR is normal or abnormal based on the symmetry of the lung regions

Vajda et al.,	2018	MC and SH	NN	78.3(MC) 95.57(SH)	0.87(MC) 0.99(SH)	Feature selection for the purpose of automatic tuberculosis screening in CXR
Sivaramakrishnan et al.,	2018	MC,SH, Kenya, India	CNN (AlexNet, VGG-16,VGG-19,Xception ,ResNet-50	0.853(AlexNet)0.855(VGG-16) 0.852(VGG-19) 0.815(Xception)0.802(ResNet)	0.926(AlexNet) 0.917(VGG-16) 0.916(VGG-19) 0.900(Exception)) 0.892(ResNet)	To compare the pre-trained deep learning models for TB detection from CXRs
Hwang et al.,	2019	SNUH, BMC,KHUG,	CNN(DLAD)	-----	0.977-1.000(classification)	To build a diagnostic tool for diagnosing active pulmonary TB based on CXRs and to test its performance using
		DEMC,MC and SH datsets			0.973-1.000(localization)	a variety of information contrasting with that of doctors
Meraj et al.,	2019	MC and SH datasets	CNN (VGG-16,VGG-19, ResNet, GoogleNet)	77.14 (VGG-16& VGG-19)(MC)86.74(VGG-16)(SH)	90.0(VGG-19)(MC)92.0(VGG-16)(SH)	To determine whether or not it is capable of producing satisfactory results despite having a limited amount of processing power and a compact model design.
Pasa et al.,	2019	MC, SH and combination of MC and SH datasets	Custom CNN	79(MC) 84.4(SH) 86.2(combined)	0.811(MC) 0.90(SH) 0.925(combined)	To build an efficient deep learning model for fast TB detection using CXRs
Hooda et al.,	2019	Private dataset	CNN Ensemble(AlexNet, Google Net, Resnet)	88.24	0.93	To develop an automatic TB classification using ensemble of deep learning architectures
Heo et al.,	2019	YU, AWH datasets	DCNN (Image CNN and Demographic variable)	-----	0.92	To propose DCNN, a combination of image CNN and demographic variable to enhance the performance of TB diagnosis
Kyung et al.,	2020	Chest X-ray14,MC,SH and JHH datasets	CNN (ResNet-50(transfer learning)	-----	0.91(SH) 0.87(JHH)	To refine dataset curation methods for automated TB screening using deep learning
Liu et al.,	2020	TBX11K	CNN	89.7	------	To provide a computer-aided diagnosis of tuberculosis based on deep learning employing CXRs
Sahlol et al.,	2020	SH and dataset2	CNN	90.2(SH) 94.1(dataset2)	-----	To demonstrate an innovative technique for the identification of tuberculosis in CXRs by utilizing artificial ecosystems to optimize DNN characteristics
Ayaz et al.,	2020	MC and SH datasets	CNN	93.47(MC) 97.59(SH)	0.97(MC) 0.99(SH)	To showcase an innovative approach for TB diagnosis that mixes hand-crafted features with deep features.

III. CHALLENGES AND FUTURE TRENDS

Despite the fact that deep learning technology has been successful in detecting PTB from CXR, there are a number of limits and obstacles that still need to be overcome in the medical and clinical fields. While CNNs are a potentially useful tool for CAD systems in the diagnosis of tuberculosis (TB), the World Health Organization (WHO) has not yet given its approval to any CAD system for use in TB detection. In order to provide approval for the using CAD in TB detection, the WHO requires more proof [6]. In the subject of automatically detecting tuberculosis using AI-based systems, this is one of the primary research gaps that new researchers are trying to fill. Researchers are focusing their efforts on developing some innovative and speedy diagnostic techniques in response to the high frequency of drug resistance (DR) in nations with an elevated rate of TB. This is because the conventional gold standard methods require a significant amount of time to complete the diagnostic procedure. During this time, there is an increased risk of disease transmission, and there is a delay in the beginning of treatment [4, 11]. Due to the fact that the deep learning system that was built by Haloi et al., [12] is trained on formal CXR pictures, the algorithm is unable to properly diagnose CXR with lateral views. As a result, one potential direction for future study is the creation of a system that uses deep learning and is able to include detection using lateral views. Children made up 1.1 million of the 10 million persons in the world who were diagnosed with tuberculosis in 2020 [1]. This percentage is attributable to tuberculosis that was either undiscovered or identified at an advanced stage, and this is because there is currently no software available for automated detection. As a result, the development of an automated technique to diagnose tuberculosis (TB) using CXR in pediatric patients is a significant research need that has to be addressed in the near future [13]. On a CXR, tuberculosis may display a wide variety of symptoms. One of the primary barriers that prevents the deployment of the CAD system that uses deep learning in real-world settings is the fact that the medical datasets that are now accessible are often inadequate and do not include all symptoms. Hence, in order to achieve a greater level of accuracy, it is necessary to create a comprehensive CXR TB database that is based on the actual world and use a hybrid approach that takes into consideration every symptom of tuberculosis [5, 7].

The examination of deep learning models needs a significant quantity of annotated data, which presents a significant problem. The annotation of photographs requires specialized expertise in addition to being labor-and time-intensive. Yet, there is a massive quantity of unlabeled data that is already accessible in the medical area. This data may be put to use by deep learning algorithms, which minimizes the amount of time and labor required [14]. As a result, unsupervised learning in deep learning is still a subject that requires more investigation. Over fitting and a lack of interpretability are two of the problems that arise when using a deep learning system in the medical industry. When a trained model does not generalize well to scenarios that have not been encountered before, yet fits the training data well, this is an example of over fitting. Using approaches such as data augmentation and weight normalization may help bring this number down. Interpretability may also be referred to as a black box, which describes a situation in which the performance of a system or how it got at the outcome is difficult to comprehend; yet, transparency is the most important component in medical diagnosis [10, 14]. The effectiveness of the algorithm is among the deep learning system's most crucial components to consider. This aspect of the system may be enhanced by using the ideas of ensemble learning and transfer learning [5]. In nations with a high incidence of tuberculosis, the implementation of a mobile device-based computer assisted system that will be accessible as a platform for open source software will be more beneficial for mass screening [3].

IV. CONCLUSION

According to the World Health Organization (WHO), tuberculosis (TB) represents a few of the diseases that pose the greatest risk to people all over the world. The majority of persons who were afflicted with the disease originated from regions that lacked resources and had medical facilities that were substandard. Because mobile computing devices provide mobile computer and communication methods and equipment for enhanced diagnosis, treatment, and prevention in these impoverished places, there is a possibility that the prevalence of tuberculosis (TB) can be reduced using these technologies. This document serves as a fast reference for researchers who are getting ready to undertake some work and outlines several elements of working.

Their investigation on the usage of deep learning methods for tuberculosis (TB) diagnosis in CXR pictures. CAD systems are being investigated in order to recognize and localize tuberculosis (TB) via the accurate screening of CXR images. The review that was conducted for this work brings to light the need of doing more research on CAD systems that make use of CXR for tuberculosis diagnosis. There is a significant amount of room for expansion in research on the deep learning to CAD-based TB diagnosis. In addition, one may draw the conclusion that an AI-based CAD system will play an important part in the identification of tuberculosis [22].

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