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A Comprehensive Study on Tuberculosis Detection Using Machine Learning Techniques

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Abstract: Tuberculosis (TB) has remained a significant global health concern for a very long time. It necessitates accurate and early detection and curing to improve patient health. This study comprehensively reviews various methods employed for detecting TB using chest X-rays. It explores traditional diagnostic approaches, including manual interpretation by radiologists, and advances in automated techniques such as machine learning (ML) and deep learning (DL) algorithms. The paper highlights the strengths and limitations of different methodologies, focusing on their accuracy, sensitivity, specificity, and computational efficiency. This study aims to offer insights into the revolution of TB detection methods and inform about developing more robust and scalable tools.

Keywords: Tuberculosis, Deep learning, Machine learning, Early detection.

I.INTRODUCTION

Tuberculosis (TB) is a respiratory illness triggered by bacteria that mainly impacts the lungs. When an individual with TB coughs, sneezes, or spits, the disease is transferred through the air. The TB bacteria is thought to infect 25% of the world's population. According to recent data, 26% of TB infections and 26% of TB fatalities worldwide occurred in India in 2023. To effectively treat the illness and stop its spread, an early and precise diagnosis is essential. The traditional approaches in TB detection rely on clinical methods such as sputum smear microscopy, culture tests, and chest X-rays interpreted manually by radiologists.

Manual interpretation of chest X-rays can be prone to errors and time-consuming, especially in regions with limited accessibility to experienced radiologists. This has led to the development of automated TB detection systems with the use of deep learning techniques. The deep learning models used in the system have achieved enormous results. The research in this area has developed several methods for the detection and classification of various diseases including TB, Pneumonia, Cardiomegaly, etc. Several of these methods include the use of machine learning and deep learning techniques for efficient detection. The learning methods often include feature extraction from the already available disease datasets and the use of image enhancement techniques such as Contrast Limited Adaptive Histogram Equalization (CLAHE), Gamma correction, Balance Contrast Enhancement Technique (BCET), etc. The phases of training of the model to detect may have some challenges including the unavailability of balanced datasets, which means it may cause bias in the detected data. This study will review the current approaches and will highlight the benefits, and challenges of the methods used in the related research.

II.BACKGROUND AND CONTEXT

Advancements in artificial intelligence and subfields such as machine learning (ML) have significantly contributed to a broad spectrum of industries. Deep Learning (DL) is considered a subfield of the vast area of Machine Learning focused on Artificial Neural Networks (ANN). The Deep Learning (DL) algorithm involves the training of ANN utilizing multiple layers to learn and recognize patterns in the given dataset. The algorithms have shown their significant impact on a wide range of applications and industries.

A. Machine Learning and Deep Learning – An overview

It's been termed that Artificial Intelligence (AI) is a combination of several fields, phrases and terms. In the context of this, Machine Learning (ML) – A subfield of Artificial Intelligence (AI) is a popular term that's been used extensively across the AI field. Machine Learning gives machines the ability to work with huge amounts of data without being explicitly programmed and without or with minimal human interventions. The machines trained will be capable of independently extracting patterns and information from the datasets fed in as inputs without the need for any external

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instructions from human agents. Another key term that is used in this field is Deep Learning (DL) – A type of ML that uses artificial neural networks to teach computers to learn and make decisions accordingly. In Figure 1, the associations among AI, ML, and DL are illustrated in depth.

The field of AI has made substantial progress in recent years, with ML and DL serving as its leading technologies. Huge volumes of data across various industries resulted in the use of ML for a variety of applications in several domains. On the other hand, Deep Learning which focuses on the utilization of Artificial Neural Networks (ANN) made significant interest across industries. The advantage of DL in processing extensive amounts of data and making decisions based on those data made it gain preference over other conventional ML approaches for efficiently managing volumes of data.

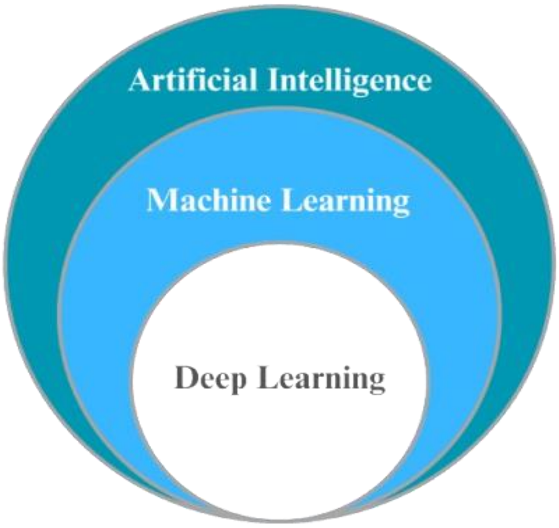

Fig. 1: AI, ML and DL relationship

Deep Learning models are often classified into six different categories, namely Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Feed Forward Neural Networks (FNN), Transformers, Autoencoders, Generative Adversarial Networks (GAN). The six categories of DL models have their own applications to meet specific requirements. CNNs are most commonly used to solve problems that involve spatial data such as images. CNNs consist of three layers, a convolutional layer, a pooling layer and a fully connected layer. Each layer of the CNN serves a specific purpose. On the other hand, a Recurrent Neural Network (RNN) is a deep neural network that is trained on time series data to create an ML model. Learning is aided by training data, and current input and output are affected by knowledge from past inputs. The Feed Forward Neural Network works based on two phases: Feedforward and backpropagation phase. The information in this network is transmitted in a single direction from the input nodes to the output nodes, passing through the concealed nodes. These networks are mostly used in pattern recognition, classification tasks, Regression analysis etc. Transformers are a kind of deep learning system that learns and comprehends context through sequential data processing using mathematical methodologies. Before the introduction of transformers, RNN was used to understand text using deep learning. Autoencoders, another type of DL model are a type of neural network architecture which is designed to efficiently compress input data to its essential features and then reconstruct the original input from its compressed representation. Mostly autoencoders are used in AI tasks related to feature extraction, image denoising, anomaly detection and facial recognition. Generative Adversarial Networks (GANs) are one of the exciting innovations in the field of AI in which the machines create new data that resemble the training data. GAN does this by combining a discriminator and generator, where the discriminator separates actual data from the generator's output while the generator learns to produce the desired output. The several kinds of AI deep learning models are depicted in Figure 2.

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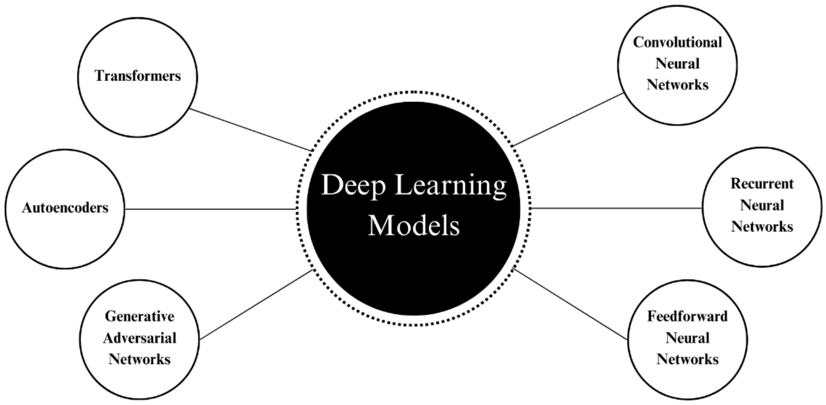

Fig. 2: Types of deep learning models

B. Significance of Artificial Intelligence in Healthcare

The health or medical industry holds a special position among industries that use various technologies and algorithms relating to ANN. Uses vary across disease diagnosis, drug discovery, and other challenging problems. Machine Learning (ML) has been utilized to promote research and development (R&D) activities in the industry. The methods employed are shown to be effective in medical professionals and hospitals by enhancing the services. ML has shown continuous improvement in analyzing medical records, identifying patterns, and creating effective treatment plans. The knowledge delivered to the doctors and professionals possesses abundant value. Together with Apollo Radiology Innovations, Google's DeepMind (Health) delivers a novel disease diagnosis tool in India. With the help of Google, the ARMMAN group has created mMitra to address maternal and child mortality. Radiology is an area of interest for implementing AI and related platforms where expertise is critical but there aren't enough radiologists to meet the needs and this often leads to delays in early detection and treatment.

C. Applications of Machine Learning & Deep Learning in Healthcare

With the progress of medical technology, the healthcare industry produces enormous amounts of data on a daily basis. There is a need to extract important information from this pile of extensive medical data. The traditional method involves the use of machine learning to extract the data, but this is a time-consuming task and requires human resources also for the analysis. Deep learning introduces cutting-edge machine-learning approach which can automatically learn complex features from variety of data sources such as medical images or texts. Some of the applications which involves the introduction of machine learning are as follows:

i.Medical Imaging

Image recognition and object detection are used extensively in the medical industry. These are used in Magnetic Resonance (MR) and Computer Tomography (CT) scans for image segmentation, disease detection and prediction. Deep learning models can work efficiently by interpreting the image data deeply to detect any anomalies. The DL models can mark areas of interest within an image can help the medical experts in the analysis of the data collected. Google's deep mind serves as a noticeable application which uses AI in collaboration with healthcare institutions to create AI models for medical imaging and their analysis. They developed a model which can detect over 50 different eye diseases using retinal scans. The model helps by assisting the healthcare professionals in diagnosing conditions in a timely manner.

ii.Drug Discovery

Deep learning bears a promise in the development and discovery of variety of drugs which involves advanced image analysis and structuring. The model used for drug discovery and manufacturing develops the molecular structure helping in the effective drug manufacturing and testing. The models developed was able to identify the structure of important drugs or combination of drugs by processing genomic and clinical datasets rapidly.

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iii.Pandemics

The models using deep learning have gained importance after the outbreak of a global pandemic such as COVID-19. Researchers studied applications in the early detection of COVID-19 by analyzing chest x-ray images. They also used different models to predict the intensive care unit admission which helps in detecting the potential COVID-19 patients. The models used was also able to predict long term consequences on the patients with disease.

iv.Robot-assisted surgery

The success of Deep Learning models specifically with image data has paved the way for the development of image-guided robots. The availability of datasets boosted the use of robots for surgical intervention. The model plays a crucial role in the surgical field by enabling automation, real-time decision making and predictive analytics. The model can also be used to analyse surgeons' performance using motion tracking features to provide the surgeon with feedback and further assist the surgeon with the whole process.

v.Tuberculosis Diagnosis & Role of Deep Learning

Tuberculosis is caused by a bacteria known as Mycobacterium Tuberculosis and mostly affects the lungs, leading to coughing and other accompanying signs like fever, fatigue, night sweats, and in the worst instances, coughing up mucus or blood. Despite being preventable and curable, TB remains a leading cause of morbidity and mortality. According to the World Health Organization (WHO), people infected with TB bacteria have a 5 – 10% lifetime risk of falling ill with TB [3] and those people with a history of other morbidities such as HIV, diabetes or people who use tobacco are at a higher risk of falling ill. Tuberculosis is misinterpreted with other diseases such as pneumonia and bronchiectasis. Historically these disease diagnoses have relied on clinical evaluation, sputum microscopy, and culture tests. Chest X-rays are a commonly used non-invasive method to analyze lung abnormalities indicating the diseases. However, this interpretation of chest X-rays requires experienced radiologists, which can be challenging in a resource-limited setting. The automation of TB diagnosis in chest X-rays has been made possible by developments in machine learning (ML) and deep learning (DL), which could increase the precision of case discoveries and prediction. The identification of tuberculosis is improved by deep learning, a branch of machine learning. This involves feature learning from balanced datasets of chest X-rays, the process is often combined with other image enhancement techniques to train an efficient model with high accuracy and generalization which can accurately and precisely detect the related diseases and other factors without or with minimum external interventions. This improves the accuracy of the clinical predictions and treatment in the context of such related diseases. In particular, ensemble learning—which combines multiple techniques to improve accuracy and robustness—has demonstrated potential. This growing interest in automated TB detection is driven by the need to enhance diagnostic efficiency, reduce the workload on healthcare professionals, and improve patient outcomes.

D. RELATED WORK

Tuberculosis detection and diagnosis using chest X-rays have been at the forefront of research for several years. Different methods have been proposed and utilized for the same, ranging from traditional clinical manual interpretations to advanced automated techniques powered by machine learning (ML), and deep learning (DL). This section of the paper reviews several key contributions in the field and reviews the methods used in the research, their advantages and drawbacks or challenges.

i. Convolutional Neural Network

This section of the paper presents a review of Neural Networks such as Artificial Neural Networks, Convolutional Neural Networks (CNN), Deep Neural Networks (DNN) etc. The review is conducted as per the aspects, methods, merits and demerits. The authors of [4] explored the method of using CNN architecture with 7 convolutional layers and 3 fully connected layers to classify the chest X-rays as either normal or TB-positive. The model was particularly trained on two publicly available datasets namely Montgomery and Shenzhen and achieved 94.73% overall accuracy and 82.09% validation accuracy using the Adam optimizer. After comparing three distinct optimizers—Adam, Momentum, and SGD—the authors came to the conclusion that Adam did the best. The architecture lies between LeNet and AlexNet in terms of complexity. In the paper [5], the authors developed and compared multiple approaches such as a custom CNN built from scratch and five pre-trained models (Inception_v3, Xception, ResNet50, VGG16 and VGG19) using transfer learning. The best results were achieved by Xception, ResNet50 and VGG16 models. The study employed data augmentation techniques to prevent overfitting and used standard image sizes of 256x256 pixels.

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ii. Ensemble Learning & Image Preprocessing – Combination review

The application of a transfer learning-based approach with the Inception_V3 model is examined in the work [6]. The technology under study uses a deep convolutional neural network (DCNN) to extract features and augment data. The study reveled that transfer learning with Inception V3 provides and effective solution in pulmonary image classification, particularly dealing with limited medical image datasets. In the paper [7], the author explores the vast area of Tuberculosis (TB) diagnostics and localization using chest X-rays. It experimented with the use of several steps that use Convolutional Neural Networks (CNN) for both TB-related abnormalities and localizing specific manifestations of the disease in chest X-rays. The study is about the modification of the CNN model structures to enhance performance by fine-tuning the models using the Artificial Bee Colony (ABC) algorithm. It enables model optimization by implementing linear average-based ensemble methods which combine the result of multiple models to reach an optimum. Another paper [8], which proposes the use of a voting-based ensemble learning method focusing on the image augmentation and preprocessing variations for TB detection; uses an ensemble of CNN. The paper employs the experiment of combining various preprocessing techniques, data augmentation strategies and fine-tuned CNN models (Inception V3 and Xception) to enhance detection accuracy. The study employs a voting-based ensemble learning strategy, where multiple models are trained with different preprocessing and augmentation variations. The best-performing models are selected as base learners for a voting mechanism, which includes both soft voting and Bayesian optimization-based weighted voting. Two TB chest X-ray datasets, Montgomery and Shenzhen, are used to test the approach.

TB detection using various methods also needs to consider the image features which play a crucial role in the accurate diagnosis and classification. On account of the image enhancement in the research, there are several processes used to employ this in the recent advancement of research. In paper [9], the study uses three different classification models- Support Vector Machines (SVM), Logistic Regression (LR), and K-nearest Neighbors (KNN) – to analyze chest X-rays. There were 138 radiographs in the datasets (80 in good health and 58 with tuberculosis). The images were preprocessed using padding and resizing techniques, and features were extracted using the ResNet50 neural network. The study implemented two classification scenarios: cross-validation and training-test set split (80%-20%). The result showed that the SVM performed best in both scenarios, achieving an accuracy of over 85% in the training-test set scenario. Another two types of papers [10,11], used the technique of feature extraction by implementing various algorithms. In [10], employs a texture-based feature approach to histogram's intensity. The method also makes use of features such as Mean, Standard Deviation (SD), Smoothness, Entropy, Root Mean Square, Variance, Kurtosis, Skewness, and Inverse Difference Moment (IDM). The accuracy of the paper was 92.86% for the Montgomery dataset and 93.94% for the Shenzhen dataset. In the paper [11], the authors propose an automatic technique to detect abnormal chest X-ray images. The suggested approach classifies or categorizes healthy and unhealthy groups using a hierarchical feature extraction strategy. A supervised classification approach is used on the extracted features to detect normal and abnormal chest X-ray images (CXR). The combination of image enhancement with other training models is often considered to provide better efficiency than any other individual models, hence the paper [12] focuses on improving TB detection from CXR using deep learning combined with image enhancement techniques. The researchers evaluated three image enhancement methods- Unsharp Masking, High-Frequency Emphasis Filtering, and CLAHE- before feeding the images into the pre-trained deep learning models – ResNet18, ResNet50, and EfficientNet-B4. The contribution was to demonstrate that proper image enhancement before deep learning can improve TB detection accuracy. In [13], the paper focuses on improving the TB screening from CXR images, particularly when dealing with out-of-domain data, that is images from different sources than the training data. The paper introduces a new processing technique known as lung BCET (Balance Contrast Enhancement Technique) that specifically normalizes the lung region of the CXR. Additionally, it developed new augmentation techniques by fusing preprocessing methods with conventional methodologies. The paper also acknowledges areas of improvement, particularly in the heatmap accuracy for their multi-augmentation approach, demonstrating transparency.

The paper [14], uses a novel approach in the detection of TB using deep neural network model. The Wide Dense Net architecture and the Convolutional Block Attention Module (CBAM) are combined in the CBAMWDNet model to improve accuracy. The researchers of this paper used a combination of various datasets available for the purpose and removed any inaccurate images. The datasets totaled to 5000 Chest X-ray images in which 3,906 was normal and 1,094 were with TB cases. On the TB dataset, the model's accuracy was 98.80%, and on the combined dataset, it was 97.00%. Additionally, when compared to other cutting-edge methods, the model performed better. In paper [15], the researchers study the detection of Tuberculosis (TB) from chest X-ray (CXR) images using deep learning employing VGG-16 Convolutional Neural Network (CNN) architecture. 700 normal and 140 tuberculosis CXR pictures from an available dataset were used in the study. The images before training were resized to 64x64 pixels. It is been observed that the paper achieved an accuracy of about 99.76% with 100% precision, 99% recall and 100% F1 score. The study outperformed several previous models for the purpose.

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E. SYSTEMATIC ANALYSIS

There are several papers which study the use of deep learning and their techniques in the field of healthcare particularly in the detection of Tuberculosis. These papers are further reviewed based on their techniques used, and the merits and demerits of the paper. The table 1 presents the comparative evaluation of the techniques developed.

TABLE I LITERATURE REVIEW

Ref. Nos.	Techniques	Merits	Demerits
Rajat Mehrrotraa et al. [16]	Employs ensemble of DCNN (DenseNet201, InceptionResNetv2, Xception) combined with classifiers such as SVM, KNN and ensemble classifier.	Achieved high accuracy of about 99.1%. The method is viable for low-resource settings. The proposed model can differentiate between TB, Covid-19 and normal CXR images.	The model is trained on limited datasets. The accuracy might get affected when the model is introduced with new unseen data.
Tao Xu et al. [17]	Computer Aided Detection (CAD) system for identifying TB cavities. Introduces coarse-to-fine dual scale technique.	Improved cavity detection which outperforms existing methods. Image segmentation is improved by the Hessian matrix method.	The model requires multiple processing stages which often increases computation time. The model is tested only on 35 CXR images which may give generalization issues.
Mostofa Ahsan et al. [18]	Explores VGG16 application. Used transfer learning with the VGG16 model on ImageNet data.	Eliminates complex preprocessing and lung segmentation. Compensates limited datasets by transfer learning.	The model is computationally intensive due to deep architecture. Significant GPU resources are required.
Sivaramakrishnan Rajaraman et al. [19]	Uses modality-specific deep learning model ensembles. Talos optimization tool was used to optimize the customized CNN architecture.Used VGG16, Inception-V3, InceptionResNet-V2, Xception, DenseNet-121.	Achieved reliable state-of-the-art performance. Reduced prediction variance and model sensitivity. Improved generalization. Cross-validation ensures robustness.	Computationally expensive to use ensemble methods. No external validation to other TB datasets. Small-size dataset used for final evaluation.
Michael J. Norval et al. [20]	Evaluates different image processing techniques for the detection of pulmonary TB using CNN. Evaluated four main approaches: image resolution optimization, pre-trained networks, hyperparameter adjustments and data augmentation.	Multiple approaches and Methodologies were tested using diverse datasets. Achieved an accuracy of about 91.04% at 64x64 resolution and 92.54% accuracy in image splitting.	The model is trained using a limited dataset and comparison with other deep learning frameworks was limited. This might cause issues in generalization.

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Pranav Rajpurkar et al. [21]	The CheXaid deep learning algorithm was created and assessed in the study. Suggested a model to assist medical professionals in identifying tuberculosis in persons with HIV.	Combined clinical and imaging data successfully. Improved accuracy over image only approach. Tested with actual clinicians in realistic scenario.	Used relatively small dataset (677 patients). Collection of diverse datasets is limited.
Vasundhara Acharya et al. [22]	The paper employs deep learning models such as CNN for feature extraction and classification. The model also uses preprocessing techniques such as contrast enhancement and noise reduction. Aims at enhancing accuracy while lowering false positives.	The model clocked high accuracy in feature extraction. The image preprocessing techniques improved image clarity, aiding in better detection. The data augmentation ensures robustness.	The model requires large labelled datasets. The model may not generalize well to all types of TB cases. May require additional optimization to avoid overfitting.
Sana Sahar Guia et al. [23]	The model uses a combination of two pre-trained models (VGG16 and VGG19) in combination with an attention mechanism. The model utilizes the ImageNet dataset and block attention module.	Achieved high accuracy of 99.66% and 99.78% for training and validation datasets respectively. Combines the strength of two proven models. A sizable dataset of 7000 photos was used by the model.	The combined model requires large computational power. Only considers two classification tasks (TB and normal). No other classification and diverse dataset were considered.
Md. Nahiduzzaman et al. [24]	The paper proposes a lightweight CNN model. The model is used to detect six types of diseases from CXR images: Pneumonia, COVID-19, Cardiomegaly, Lung Opacity, Pleural, and Normal cases. The model also uses Grad-CAM visualization to highlight the infected areas in images.	The model achieved high accuracy in binary classification (97.94%). Also, the model clocked good performance in multiclass classification (80%). Highlights infected areas in CXR images. The model outperforms existing models.	The model has lower multiclass accuracy compared to binary classification. The model may face performance issues while introducing diverse datasets.
Goram Mufarah M. Alshmrani et al. [25]	The proposed model utilizes VGG19 architecture combined with CNN. The model is used to classify six categories of disease: pneumonia, lung cancer, TB, lung opacity, Covid-19 and normal cases.	The accuracy and degree of precision of the model were 97.56% and 96.48%, respectively. The model employs the classification of multiple diseases in a single model. Utilized a large dataset of 80,000+ images.	Dependency on large diverse dataset which may affect generalization. Requires significant computational power.
U.K. Lopes et al. [26]	The paper proposes three different approaches to utilize pre-trained CNNs (GoogleNet, ResNet, VGG Net) combined with Support Vector Machine (SVM).	Better performance compared to existing methods or models. Large labeled datasets are not as necessary when using a pre-trained model.	Limited generalizability due to reliance on limited datasets (Montgomery and Shenzhen). The model diversity is limited.
Evans Kotei et al. [27]	The U-Net model was utilized in the study to segment the lungs. Eight different CNN models were used for feature extraction. A stacked ensemble algorithm approach was developed to combine outputs of multiple models.	High segmentation accuracy of 98.58% and classification accuracy of 98.38% were demonstrated by the method. The model is effective for early detection of TB with limited resources.	Requires enormous computational resources for training and validation. Limited generalization on unseen data.

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Quang H. Nguyen et al. [28]	The paper proposed transfer learning with a focus on multiclass multilabel training. Inception ResNet, VGG16, VGG19, DenseNet-121, and ResNet50 were among the architectures employed in the study.	The model has improved classification performance. The model enhanced interpretability through CAMs.	The model has the potential to overfit with complex models. High computational resources are required.
Sahar Kazemzadeh et al. [29]	The model used a deep learning system trained on CXR images from 10 countries. It employed techniques such as Large-scale pretraining, attention pooling and semi-supervised learning.	The model showed a high sensitivity of 88% and a non-inferior specificity of 79%. It is generalizable across diverse population.	Performance may vary across different populations. Need a significant amount of processing power to train and validate the model.
Quang H. Nguyen et al. [28]	The paper proposed transfer learning with a focus on multiclass multilabel training. Inception ResNet, VGG16, VGG19, DenseNet-121, and ResNet50 were among the architectures employed in the study.	The model has improved classification performance. The model enhanced interpretability through CAMs.	The model has the potential to overfit with complex models. High computational resources are required.
Thi Kieu Khanh Ho et al. [30]	The paper focuses on the application of deep convolutional neural networks (DCNN) such as ResNet152, Inception-ResNet, and DenseNet121. It employed various preprocessing techniques including data augmentation and t-SNE visualization.	High detection accuracy with DenseNet121 achieving an AUC of 0.95. The model performs better thanks to its efficient use of data augmentation.	Limited generalizability due to reliance on specific limited datasets. Potential overfitting if not enough diverse data is used for training. Also requires enormous computational resources.
Seowoo Lee et al. [31]	The model proposed by the authors used a deep neural network using a large dataset of radiographs. The model was designed to detect active and healed TB.	The model has a high sensitivity of up to 98% and specificity of 76%. The model addresses the variability in human interpretation of radiographs.	The model has limited generalizability due to limited datasets. Requires substantial computational resources.
Chutinun Prasitpuriprecha et al. [32]	Using a variety of CNN architectures, the authors of the research created a TB/non-TB detection and drug-resistant classification decision support system (TB-DRC-DSS).	The model's categorization accuracy was high, at roughly 92.6%. It showed improved performance compared to existing methods (43.3% average improvement).	Requires huge computational resources. Performance may vary with different datasets and populations.
Zhi Zhen Qin et al. [33]	The paper evaluates the performance of three DL models: CAD4TB, Lunit INSIGHT and qXR in detecting TB from CXR images.	High diagnostic accuracy with AUC values of 0.94 for Lunit and qXR and 0.92 for CAD4TB.	Variability in performance based on population characteristics and prevalence of TB. Limited generalizability.
Yu Cao et al. [34]	The authors of the paper propose a socio-technical system which integrates CNN with mobile health technologies. It reports on the development of a large-scale annotated CXR image database	The paper addresses critical barriers to TB diagnosis by providing a comprehensive image database. It proposes collaborative approach involving both computer	Reliance on the number and quality of the database of tagged images for training the model. Challenges in deploying mobile health solutions in diverse clinical settings.

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	and the creation of computational models to classify TB from CXR images.	scientists and health professionals.	
M.P. Rajakumar et al. [35]	The proposed system consist of phases such as: image collection, preprocessing, feature extraction using deep learning models VGG16 and VGG19, optimal feature selection using the Mayfly algorithm, serial feature concatenation and binary classification with K Nearest Neighbor (KNN) classifier.	The proposed model achieved a high classification accuracy of about 97.8% for TB detection. The optimal feature selection using the Mayfly algorithm improves model performance.	Computationally demanding because deep learning methods are used. Potential overfitting if not properly managed during training. Limited generalizability if applied to different populations without further validation.
Michael J. Norval et al. [36]	The paper investigates the precision of detecting pulmonary TB using CXR images through CNN. It evaluates factors such as image dataset resolution, pre-trained networks (AlexNet, VGG16 and VGG19), hyperparameter changes and data augmentation.	The proposed model used pre-trained networks to improve accuracy. Data augmentation leads to better feature extraction.	No significant improvement observed; networks may not be tuned for medical images. Higher resolutions may lead to overfitting due to irrelevant features. Requires careful implementation to avoid introducing noise or artefacts.
SoYeon Choi et al. [37]	Using a tailored multimodal approach, the study created a model to forecast pulmonary tuberculosis culture test results. It integrated the method with automated detection algorithms (DLADs) based on deep learning.	The method enhances chest radiograph interpretation which leads to better decision rates. The model allows for the identification of significant clinical factors associated with pulmonary TB.	More intricate interactions between variables might not be captured by the model. Limited by quality and completeness of historical data.
Seelwan Sathitratanacheewin et al. [38]	The study by the authors investigates the generalizability of a Deep CNN model for detecting TB in CXR images. The authors developed a DCNN model using TB specific CXR dataset from Shenzhen No.2 Hospital.	The model achieved an AUC of 0.9845 in the training dataset and 0.7054 in the external dataset. The study highlights the impact of different populations on model performance.	Due to distribution shifts, the model might not generalize well to external datasets. The model may not capture all aspects of model performance in clinical settings.
Mayidili Nijiati et al. [39]	The authors of the paper developed a segmentation model named TB-UNet utilizing ResNeXt as the encoder. The dataset comprised 2627 TB positive and 7375 TB negative cases for training and 276 TB positive and 619 TB negative cases for testing.	The model achieved a high accuracy of about 85% compared to radiologists (62%) without AI. The model developed effectively detects diseased regions in CXR images. It also improves diagnostic sensitivity by 11.8% with AI assistance.	The model has a dependence on the quality of training data; and may not generalize to all populations. This may lead to over-reliance on AI predictions without thorough human review.
Garima Verma et al. [40]	The paper aims to detect TB at an early stage by analyzing chest X-ray images using a deep neural network. The Synthetic Minority Oversampling Technique (SMOTE) was used to resize the photos to 224 by 224 pixels,	The model achieved a high accuracy of 95.7% without filters and 97.9% with filters and edge detection techniques. Gabor Filters and Canny Edge detection enhances feature extraction, improving model	The model requires a large dataset for training; and may not generalize well to all populations. The filters are computationally intensive; and may introduce noise if not applied correctly. Actual

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	normalize them, and balance them in the model. The paper employed pre-trained models such as DenseNet169 and MobileNetV2 along with Gabor filters and Canny edge detection for feature extraction.	performance. SMOTE addresses class imbalance, improving model training.	scenarios may not always be accurately captured by synthetic data.
James Devasia et al. [41]	The paper focuses on the use of deep learning algorithms to classify manifestations of active TB in lung zones using chest X-ray (CXR) images. The EfficientNetB4 algorithm was employed, utilizing transfer learning for improved classification performance.	The model showed high accuracy in classifying TB manifestations. The multi-label classification is capable of detecting multiple TB manifestations simultaneously. The Grad-CAM visualization provides interpretability of model predictions, aiding clinical acceptance.	For both training and inference, the model needs a significant amount of processing power. Complexity in model training and evaluation; may require extensive labeled data.
Shufan Liang et al. [42]	The paper discusses the development of deep learning based system known as DeepTB. The model is designed to diagnose drug-resistant TB and classify its subtypes using chest computed tomography (CT) images. ResNet was used in the model's construction.	The model achieved high diagnostic accuracy (AUC of 0.943 for DR-TB diagnosis). The range of AUCs for the classification of DR-TB subtypes is 0.880 to 0.928. Provides visual explanations (CAMs) to assist radiologists in interpreting results.	Limited to a single hospital dataset, which may affect generalizability to other populations. Potential bias due to the demographic homogeneity of the dataset.Reliance on manual annotation may introduce variability and subjectivity in training data.
Chih-Ying Ou et al. [43]	The authors of the paper utilized various U-Net-based models, including U-Net, attention U-Net, U-Net++, attention U-Net++ and PSP attention U-Net++ to classify and segment two specific types of TB lesions: Infiltrations/bronchiectasis and opacity/consolidation.	The model achieved high accuracy and performance metrics (1.0 accuracy). Effective detection and segmentation of TB lesions, providing detailed information to clinicians. Using several deep learning models improves performance and resilience.	Limited to only two types of TB lesions, reducing the applicability of the method. Potential overfitting due to a relatively small dataset size (222 images). Variability in image quality may affect performance.
Shufan Liang et al. [42]	The paper discusses the development of deep learning based system known as DeepTB. The model is designed to diagnose drug-resistant TB and classify its subtypes using chest computed tomography (CT) images. ResNet was used in the model's construction.	The model achieved high diagnostic accuracy (AUC of 0.943 for DR-TB diagnosis). The range of AUCs for the classification of DR-TB subtypes is 0.880 to 0.928. Provides visual explanations (CAMs) to assist radiologists in interpreting results.	Limited to a single hospital dataset, which may affect generalizability to other populations. Potential bias due to the demographic homogeneity of the dataset.Reliance on manual annotation may introduce variability and subjectivity in training data.

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III.CONCLUSION

Tuberculosis (TB) remains a persistent global health challenge, necessitating early and accurate detection to prevent its spread and improve treatment outcomes. Traditional diagnostic techniques such as sputum smear microscopy and radiologist-assisted chest X-ray interpretations, though widely used, are often time-consuming, prone to errors, and inaccessible in resource-limited settings. The advent of machine learning (ML) and deep learning (DL) techniques has introduced a paradigm shift in automated TB detection, enhancing diagnostic efficiency and accuracy.

This study provided a comprehensive review of various ML and DL methodologies employed for TB detection. Convolutional Neural Networks (CNNs), particularly architectures like VGG16, ResNet, Inception-V3, and Xception, have demonstrated high accuracy in classifying chest X-ray images as TB-positive or normal. Ensemble learning approaches, integrating multiple models to refine predictions, have further improved the robustness and generalizability of TB detection systems. Additionally, advanced image preprocessing techniques such as Contrast Limited Adaptive Histogram Equalization (CLAHE), Balance Contrast Enhancement Technique (BCET), and high-frequency emphasis filtering have been found to enhance feature extraction and improve model performance.

Despite these advancements, several challenges persist. One major limitation is the reliance on large, well-annotated datasets. Many studies utilize publicly available datasets such as Montgomery and Shenzhen, which, while useful, may not be fully representative of diverse populations. This lack of dataset diversity can affect the generalizability of models when applied to real-world clinical settings. Another challenge is the computational cost associated with deep learning models. High-performing architectures such as ensemble learning models and CNN-based approaches require significant computational resources, which may not be feasible for widespread deployment in low-resource healthcare settings. Overfitting is another concern, especially when models are trained on small or imbalanced datasets.

Future research should focus on addressing these challenges through several approaches. First, the creation of larger, more diverse TB datasets covering different demographics and clinical conditions can improve model robustness. Additionally, the integration of explainable AI (XAI) techniques can enhance the interpretability of ML models, making them more reliable for adoption in clinical practice. Transfer learning and domain adaptation techniques can also be explored to improve the model's ability to generalize across different datasets. Furthermore, the implementation of lightweight deep learning models optimized for edge computing and mobile healthcare applications can enable real-time TB detection in remote and underprivileged areas.

In conclusion, machine learning and deep learning have significantly improved the accuracy, efficiency, and accessibility of TB diagnosis. While current advancements show great promise, continued efforts are needed to address the limitations related to dataset availability, model generalizability, and computational efficiency. By integrating AI-driven TB detection with real-world clinical validation and technological optimizations, future developments can play a crucial role in global TB eradication efforts, ultimately reducing morbidity and mortality associated with the disease.

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