IJFANS INTERNATIONAL JOURNAL OF FOOD AND NUTRITIONAL SCIENCES
ISSN PRINT 2319 1775 Online 2320 7876
 UGC CARE Listed (Group -I) Journal Volume 11, Iss 11, 2022

Revolutionizing Tuberculosis Diagnosis: A Comprehensive Review of Artificial Intelligence Advancements

Nisha[1], Dr. Reena[2]
[1]Research Scholar, Department of Computer Science and Applications, Baba Mastnath University, Rohtak, Haryana, India
[2]Assistant Professor, Department of Computer Science and Applications, Baba Mastnath University, Rohtak, Haryana, India

Abstract: Tuberculosis (TB) remains a significant global health challenge, with millions of new infections reported annually. In this review paper, we explore the evolving landscape of TB diagnosis, focusing on the pivotal role played by artificial intelligence (AI) in addressing the complexities associated with this chronic infectious disease. The paper begins with an overview of TB, highlighting its prevalence, transmission, and the emergence of drug-resistant strains, underscoring the urgent need for innovative diagnostic approaches. The review delves into the limitations of conventional diagnostic methods and introduces the potential of computer-aided diagnostics (CAD) tools as a transformative solution. A detailed analysis of recent research efforts showcases various AI-based models that have demonstrated high performance in TB detection. These models employ advanced techniques such as image pre-processing, lung field segmentation, and feature extraction to enhance diagnostic accuracy. The integration of deep learning, fuzzy logic, genetic algorithms, and artificial immune systems into AI models is discussed, showcasing their ability to improve specificity and efficiency in TB diagnosis. Furthermore, the review explores the development of mobile health technologies leveraging deep learning to address diagnosis challenges in marginalized and developing regions. The airborne nature of TB transmission and risk factors associated with active and latent TB cases are outlined to provide context for the importance of early and accurate diagnosis. The paper also discusses the various manifestations of TB, including extra pulmonary tuberculosis (EPT) and military tuberculosis, emphasizing the need for precise diagnostic tools. The classification of TB into multidrug-resistant TB (MDR-TB) and extensively drug-resistant TB (XDR-TB) is explored, highlighting the impact of irregular treatment and drug supply issues on the emergence of resistant strains. The review concludes with a reflection on the promising advancements in AI-driven diagnostic tools, such as CAD4TB, Lunit INSIGHT, and qXR, and their potential to reshape the landscape of TB diagnosis, offering hope for more effective and timely interventions.

Keywords: Tuberculosis, diagnosis Tuberculosis treatment, artificial intelligence (AI),deep learning

I INTRODUCTION

The germ that causes tuberculosis (TB), which is also written as Mycobacterium tuberculosis (MTB), is one that is hard to get rid of. The bacteria can live in both extracellular and intracellular settings [1]. They have a slow growth rate. Viruses can also go into the delay phase when the host's immune system is weak, and they can quickly return to the exponential growth phase [2]. It was reported by the World Health Organization (WHO) in 2019 that about 10.0 million people had contracted TB and 1.4 million had died from it [1]. Further, tuberculosis is the main cause of death in the world, which makes it a global health

emergency, especially for people with HIV and weak immune systems [3]. Also, developing countries are more likely to have TB than developed ones because they don't have enough trained radiologists and medical equipment [4]. There are also a lot of people in developed countries who get tuberculosis.

The problem of controlling tuberculosis is also made worse by mycobacterium strains that are multidrug-resistant and highly drug-resistant [5]. In many cases, the disease is likely to get worse by turning into a type of tuberculosis that can't be treated with any drugs [2]. Identifying MTB strains that are hard to treat and diagnosing people earlier will be one of the biggest problems in the next few decades. It is possible that artificial intelligence (AI) could help solve the problem of tuberculosis (TB).

Utilising computer-aided diagnostics (CAD) tools has greatly improved the understanding of medical images and has the potential to help doctors find cases of tuberculosis (TB). This year there has been a lot of work on researching and developing a high-performance diagnosis system. As an example, a CAD model was made to help figure out what was wrong with the TB pocket. This model was able to find important parts of the chest X-ray picture. It gets rid of the issues with previous CAD systems, which couldn't find the TB holes because they had overlapping anatomical parts in the lung area [6]. In the same way, a CAD programme that could directly find TB was created. Because of its advanced features, this algorithm was able to identify and extract images of ribs from chest x-rays. Because of this new idea, a clear picture of the lung surface could be obtained in order to find lesions or opaque masses. This eventually led to a more accurate diagnosis of TB [7]. Artificial intelligence (AI) programming has recently improved, allowing the creation of programmers that can find more TB symptoms. Following the same ideas, a TB detection channel was created by combining different methods such as chest x-ray analysis, texture analysis, and filtering. The programme was mostly focused on cavitary features and lesions, and it took into account all the different ways that TB could show up [8].

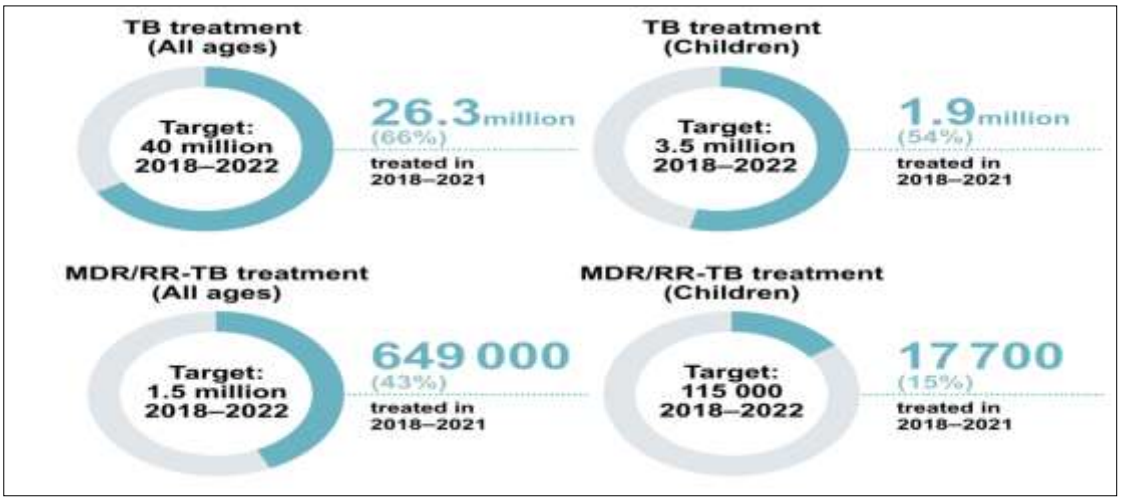

Fig. 1 the number of people treated for tuberculosis around the world between 2018 and 2021 compared to the goals set at the UN high-level meeting on TB in 2018–2022.

An advanced CAD system was created, and the model in this system preprocessed the chest X-ray images. The picture quality got better as a result. Additionally, the newly created algorithm split the lung field and gathered the important details as a first step. Later, a classifier was used to check these traits to see if TB was present. It was able to get a 95.6%

success rate [10] by using the Shenzhen and Montgomery databases [9], which have also been used in other deep learning methods. As algorithms, also known as "deep learning models," get more complicated, it gets easier for doctors to do their jobs accurately. Mixing deep learning with fuzzy logic, genetic algorithms, and an artificial immune system has created a number of simple processes that have improved both the accuracy and range of TB tests. An economic downturn and developing country made a mobile health device using deep learning to help with TB detection. The goal was to shorten the time it took to identify tuberculosis, which can be fatal, by creating a tech-socio system that could sort chest X-ray images into the different forms it can take. [11]. Using deep learning, a brand-new way to check for TB was also created. An individualized screening system was used for this method to focus on lesions. The model was used to automatically pull out features from the given data. The features that were pulled out based on the target. The majority of TB cases that are recorded are in adults (Fig. 2). Globally, 57% of people who were told they had a new or relapsed case of TB were men, 36% were women, and 6.9% were children (0–14 years old). Adult national TB prevalence surveys have found higher male-to-female ratios. This suggests that notification data may not fully reflect the load of TB disease that men carry.

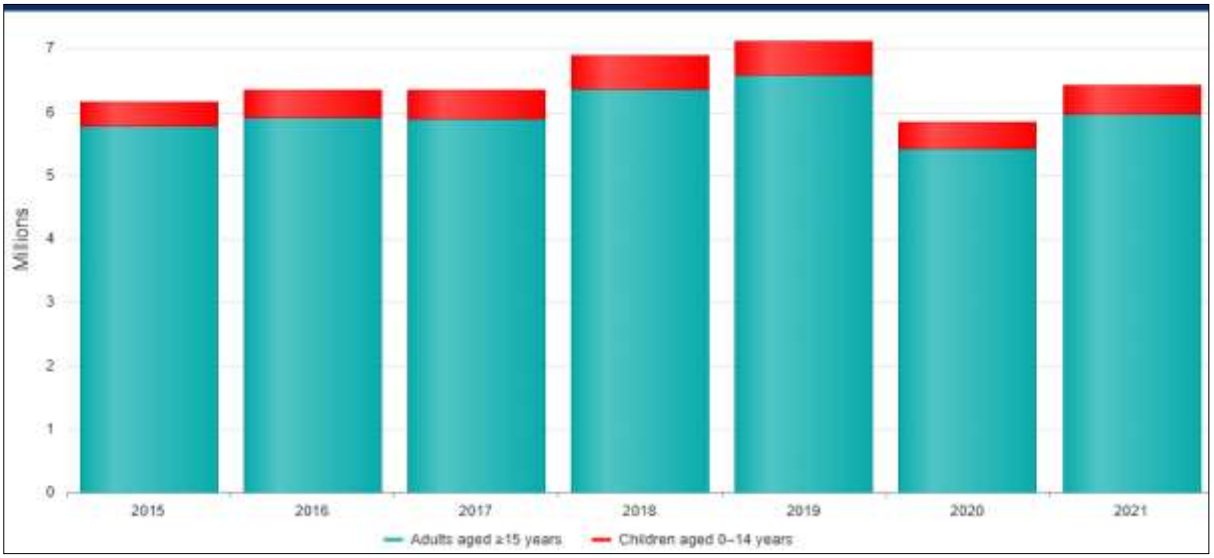

Fig. 2 the global number of people reported to have been treated for TB disease, 2015–2021

The global male: female (M:F) ratio for TB notifications in 2021 was 1.6. The distribution of notified cases by age and sex varies among WHO regions

Tuberculosis (TB) and Its Occurrence

A bug called Mycobacterium tuberculosis (MTB) causes TB, which is spread through the air. This illness mostly affects the lungs [13]. Although, the bacteria can also travel from the lungs to other parts of the body through different routes, such as the intestines, the skeleton, the brain, and the gland. Persons who have tuberculosis release the bacteria when they cough, sneeze, or spit. Individuals who are healthy can get tuberculosis (TB) from breathing in these germs, even in very small amounts (14). “Latent TB” (LTB) patients are people who have tuberculosis but don't have any symptoms [16]. “Active TB” (ATB) patients are people who do have symptoms [15]. Although people who have dormant tuberculosis can't infect others, they are much more likely to get the disease themselves if they don't live healthy lives (Figure 3). Also, people whose immune systems are weak because of diabetes, HIV, poor nutrition,

ISSN PRINT 2319 1775 Online 2320 7876
 UGC CARE Listed (Group -I) Journal Volume 11, Iss 11, 2022

or a habit of smoking are more likely to get TB if they come into contact with someone who has it [17]. Excess pulmonary tuberculosis (EPT) happens when the bacteria can get into areas other than the lungs, like the brain, spine, and bones. Within the very rare type of active tuberculosis called "military tuberculosis," the mycobacterium moves through the bloodstream to different parts of the body. A very dangerous type of tuberculosis because it attacks many systems at once, like the heart, spinal cord, and lungs [18]. Different types of active tuberculosis are multidrug-resistant tuberculosis (MDR-TB) and extremely drug-resistant tuberculosis (XDR-TB). Initial ant tuberculosis drugs don't work on MDR-TB. This resistance could happen because the patient isn't getting enough or good enough drugs for the treatment, or it could be because the therapy isn't happening regularly. All drugs used to treat tuberculosis can't kill XDR-TB, even the ones that are initially and secondarily recommended (capreomycin, kanamycin, and amikacin) [19].

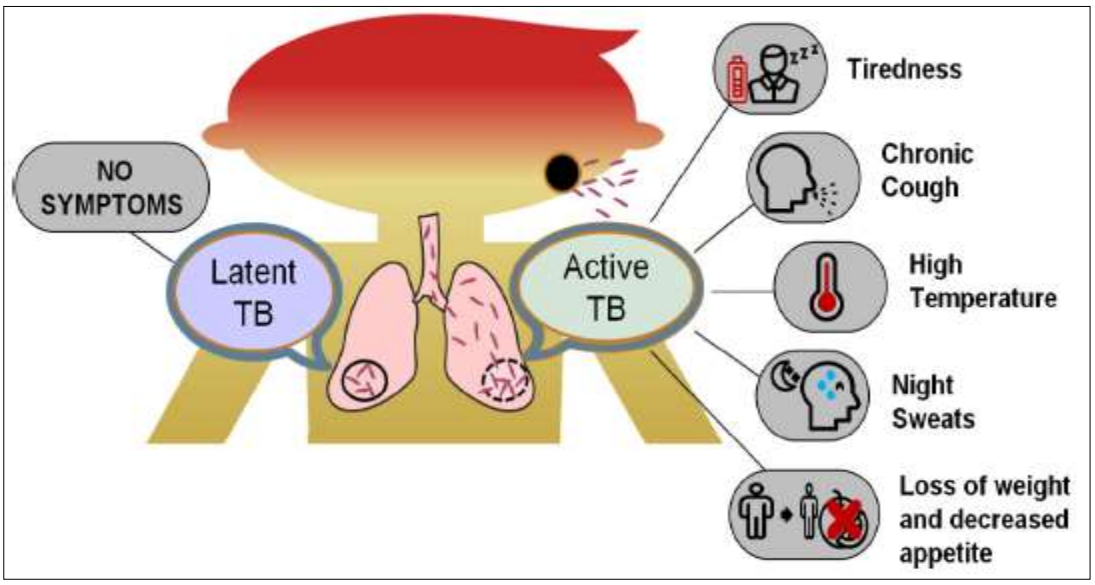

Fig. 3 Diagrammatic representations of symptoms of active and latent TB.

Conventional Diagnostic Techniques for Pulmonary TB

Finding lung tuberculosis early is better for treating the disease. Along with improving the patient's health, it also improves the health of everyone else in the community because it lowers the chances of spreading disease [20]. Finding out if someone has tuberculosis (TB) requires looking at a number of related symptoms and important details from their medical background. The slow growth of bacteria in a patient's lungs, which happens a long time before any symptoms of the disease show up [21], is what makes early TB detection frustrating. The different tests used to find TB are chest X-ray [22], conventional light microscopy [23], light-emitting diode (LED) fluorescence smear microscopy [23], [24], liquid culture with drug susceptibility testing (DST) [25], lipoarabinomannan (LAM) lateral flow assay [26], Xpert MTB/RIF [27, first-line (FL) line probe assay (LPA) [28], second-line (SL) line probe assay (LPA) [29], and Loop amp [30] The Mycobacterium tuberculosis complex test Screening for pulmonary tuberculosis (TB) early on includes a microscopic examination, sputum cultures, and lung X-rays. Alternatively, a drug sensitivity test (DST) finds strains that are no longer sensitive to drugs [21]. Conventional methods are hard to use, take a long time, and need extra time to understand reports when it comes to diagnosing diseases and finding treatments that don't work. In addition, early disease discovery can be

ISSN PRINT 2319 1775 Online 2320 7876
 UGC CARE Listed (Group -I) Journal Volume 11, Iss 11, 2022

slowed down, which can hurt the patient and spread the disease to nearby healthy people [31]. In response, many diagnostic methods have been created to quickly diagnose tuberculosis (TB). It takes less time and has a higher level of awareness to use these methods [32]. Unfortunately, these tests are very expensive for labs and need very skilled workers, as shown in Table 1 [33].

Table 1. Limitations of conventional methods used in TB diagnosis.

Test	Principle	Detects	Drawbacks	Refs.
Chest X-ray	Imaging of inflammations in the lungs	Active tuberculosis	There is not a lot of accuracy or sensitivity. You can't study EPT.	[22]
Conventional light microscopy	Using a light microscope, the mycobacterium in the phlegm smear can be seen.	Active tuberculoss	Low sensitivity in cases where HIV and TB co-infection is present.	[23]
Fluorescent LED microscopy	Therefore, fluorescence imaging is used to see the mycobacterium in the sputum sample.	Active tuberculosis	A difficult job that takes a lot of time. An expensive price.	[23,24]
Liquid culturing with Drug susceptibility testing	When growing Mycobacterium, liquid media is employed as the medium.	active tuberculosis and medication resistance	A difficult job that takes a lot of time.	[25]
Lipoarabinomannan lateral flow assay	Detects antigen	Even though a person has HIV, they can still have active TB.	A lot of money needs to be spent in order to make a laboratory. needs to be done by skilled workers	[26]
Xpert MTB/RIF	Nucleic acid growth test using quantitative polymerase chain reaction	Drug resistance, especially to rifampicin, and active TB	It can cost a lot of money to open a laboratory. Needs trained staff to be used.	[27]
Line probe assay for drug resistance to first-line anti-TB drugs (FL-LPA)	Test for the amplification of nucleic acids using the line probe assay	Active tuberculosis and drug resistance to anti-TB medications considered to be first-line treatments	The cost of setting up a laboratory is very high.Calls for hiring people who are informed.	[28]

Line probe assay for drug resistance to second-line anti-TB drugs (SL-LPA)	Find out if nucleic acids have been amplified using the line probe test.	actively spreading tuberculosis and drug resistance to second-line treatments for TB, such as injectable	It can be very expensive to open a lab. Involves hiring people with the right skills.	[29]
Loopamp M. tuberculosis complex assay	As a test, loop-mediated isothermal amplification was used to make nucleic acid copies.	Active tuberculosis	It can cost a lot of money to open a laboratory. Needs trained staff to be used. Being unable to find drug resistance.	[30]

History of AI Applications in TB Diagnosis

Researchers have utilized artificial intelligence (AI) in tuberculosis (TB) diagnosis, leveraging neural networks and their improved versions for pattern recognition in chest X-ray images. In the early 1990s, artificial neural networks (ANN) emerged for TB diagnosis, distinguishing between interstitial lung diseases and identifying TB bacillus in sputum smears. Machine learning programs, including support vector machine, decision tree, and random forest, were also employed for TB diagnosis. However, the challenge remained in achieving accurate predictions. The introduction of deep learning (DL) in the early 2010s marked a significant advancement, integrating neural networks with algorithms like genetic algorithm and fuzzy logic. DL approaches demonstrated the capability to predict and evaluate complex data, addressing challenges such as drug resistance. In 2017, a DL model accurately predicted multidrug-resistant TB from computed tomography images. DL in TB diagnosis expanded to predicting severity from CT pulmonary images, enabling fast screening and evaluation of chest radiography. Notable DL tools, including CAD4TB, Lunit INSIGHT, qXR, InferRead DR Chest, emerged for efficient and rapid TB predictions.

II Research methodology

These reviews are meant to give you an idea of the different machine-learning and deep neural network methods that are used to find diseases in rice plants by looking at pictures of sick plants.

The methodology of review consists following steps:

Data Collection: Identify sources of data, including academic journals, books, clinical databases, government health records, and international health organizations.

Searched Databases: Five sources were used for this literature review: Science Direct, Scopus, Springer, ACM (Association for Computing Machinery), and IEEE (Institute of Electrical and Electronic Engineers), which is part of the IEEE Explore Digital Library. Time periods ranging from 2015 to 2022 were chosen for this study.

1.

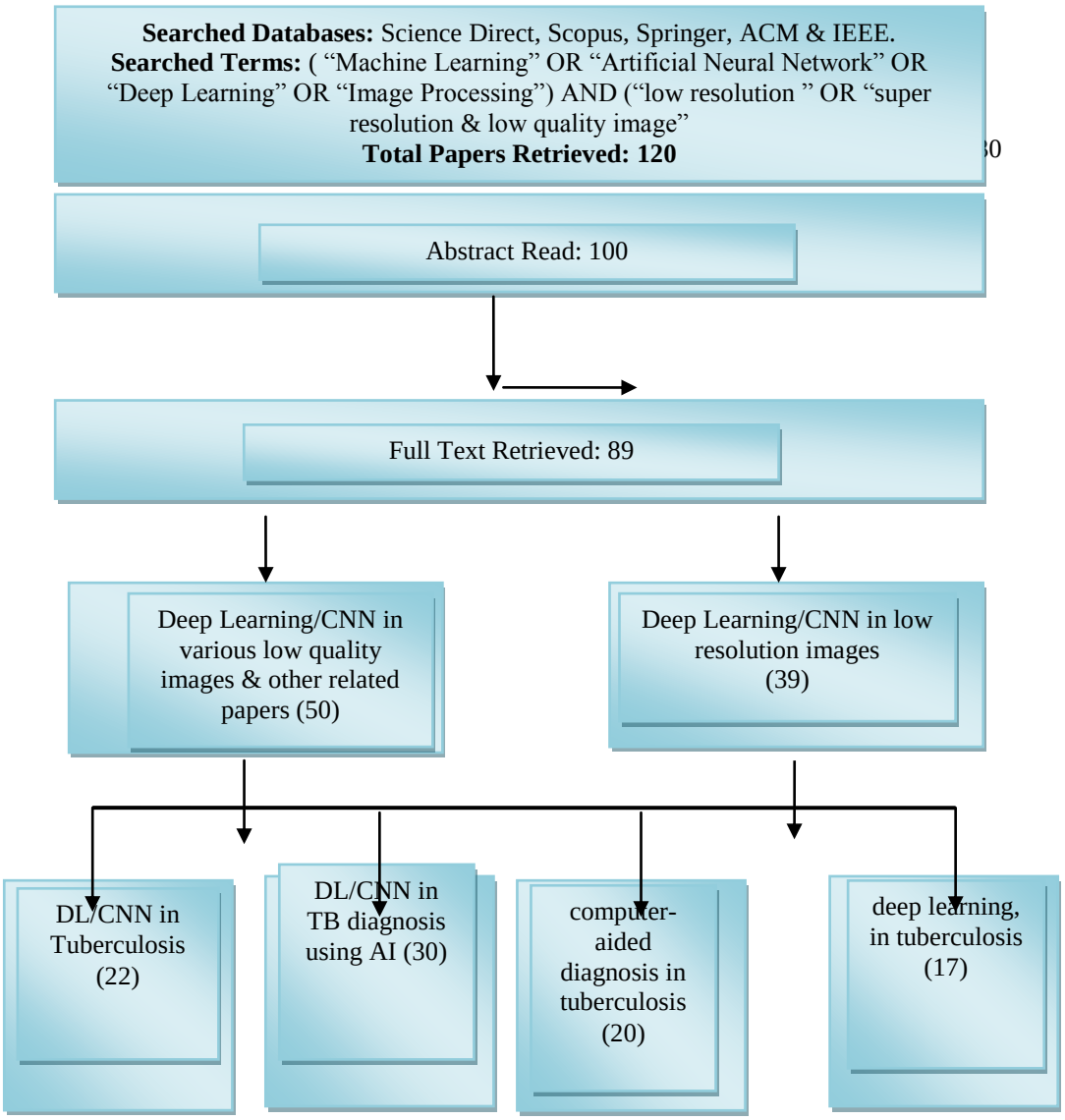

Figure 4: Research Methodology Flow

Searched Terms: When conducting a study on improving low-quality images using deep learning, researchers might use specific keywords and phrases to search for relevant literature. Some potential search terms could include:

Tuberculosis pathogenesis Immunology Tuberculosis diagnosis Tuberculosis treatment

Inclusion Criteria: Studies related to the application of AI, particularly deep learning, in the diagnosis of tuberculosis. Research focusing on advancements and innovations in TB diagnosis using AI. Articles providing comprehensive reviews or analyses of AI technologies in the field of TB diagnosis.

Exclusion Criteria: Studies unrelated to the application of AI, deep learning, or computer-aided diagnosis in tuberculosis. Research not specifically addressing advancements in AI technologies for TB diagnosis. Articles lacking relevance to the specified search terms.

Data Analysis: Evaluation of selected studies will involve summarizing key findings related to AI technologies used in tuberculosis diagnosis. Identification of common trends,

challenges, and successes in the integration of deep learning in TB diagnostics.
Analysis of data regarding the performance and impact of AI models on tuberculosis diagnosis.

Purpose of the Study:

- To provide a comprehensive review of the current state of artificial intelligence advancements in tuberculosis diagnosis.
- To identify key challenges and opportunities in applying deep learning to improve TB diagnostics.
- To offer insights into the potential of AI technologies in revolutionizing TB diagnosis.

Deep Learning Architecture: Investigation into the types of deep learning architectures utilized in the selected studies, such as convolutional neural networks (CNN), recurrent neural networks (RNN), or other relevant architectures. Examination of how these architectures contribute to the accuracy and efficiency of tuberculosis diagnosis.

Overview of AI Techniques Used in TB Diagnosis

AI and machine learning algorithms encompass various techniques crucial for tuberculosis (TB) diagnosis. Basically, there are three types of education: learning with supervision, learning without supervision, and learning with some supervision, each with distinct advantages and applications.

Supervised Learning:

This method involves a set of input data (X) and output data (Y). A CAD system for TB diagnosis utilized supervised learning, combining deep and hand-crafted features. The model, employing pre-trained CNN frameworks, demonstrated efficient early screening capabilities.

Unsupervised Learning:

In unsupervised learning, only input data (X) is available without comparable output data. This method trains models to extract features for clustering data into different units. Models in Bogota, DC, and Rio de Janeiro utilized supervised learning for disease diagnosis and unsupervised learning for data clustering, showing promising specificity and sensitivity for TB diagnosis.

Semi-Supervised Learning:

Using both marked and unlabeled data is part of learning through semi-supervision. This approach works for many real-life problems, enhancing accuracy even with limited labeled data. For TB diagnosis, a study used semi-supervised learning to train a model on chest X-ray images, achieving good accuracy and reducing the need for large, organized datasets.

Transfer Learning:

Transfer learning, a popular technique, allows the model to learn from existing data and transfer knowledge to new sources. In TB diagnosis, transfer learning was applied to chest X-ray images, achieving high accuracy, sensitivity, and specificity. This technique is valuable for improving predictive efficiency in target sources.

Table 2. Analyzing the pros and cons of the different machine learning methods used to diagnose tuberculosis.

S.No.	Learning Technique	Merits	Limitations	Refs.
1	Supervised Learning	Excellent accuracy Based on training with previous data, helps find answers to	A name is needed to be able to use training data. Somewhat enough high-quality material is	[46]

		problems	needed.	
2	Unsupervised Learning	With undetermined or raw info, it works great.	There is something wrong with this. The final data can't be chosen with this method, but it can with the supervised method.	[48]
3	Semi-supervised Learning	This programme can use both marked and unlabeled data at the same time.	Problems managing info that can't be seen.	[49]
4	Transfer Learning	The time needed to build a model is shortened.	For the model to work, the problems in both the input model and the goal model must be quite similar.	[50]

III LITERATURE REVIEW

The presented studies collectively emphasize the critical impact of diseases on apple and mango crops, recognizing the economic and agricultural significance of these fruits. Researchers propose innovative solutions leveraging machine learning (ML) and deep learning (DL) techniques to detect and categorize diseases affecting these fruit-bearing plants. Here is a brief summary of each study:

Soarov Chakraborty et al. (2021): Recommends a system combining ML and image processing for efficient classification of infected and non-infected apple leaves. Utilizes image processing techniques such as Otsu thresholding and histogram equalization. Achieves 96% accuracy in disease type recognition using Multiclass SVM.

Bajjuri Usha Rani et al. (2021): Examines the epidemiology, pathogenesis, and consequences of various apple plant diseases using ML and DL. Stresses the need for automated disease detection methods to prevent financial losses and maximize fruit yield

Barsha Biswas et al. (2022): Highlights the importance of early disease detection in agriculture to maintain high crop yield. Presents an apple tree disease detection model based on Multilayer CNN, outperforming traditional ML algorithms.

S. Dhanasekaran et al. (2022): Proposes a system for identifying plant diseases in various crops, including apple, using both ML (Support Vector Machine) and DL (Convolution Neural Network) techniques.

Harshit Singh et al. (2022): Focuses on the classification of diseased and healthy apples using DL (ResNet 50) and multiclass classification. Analyzes performance metrics to evaluate the accuracy of the proposed model.

Sachin Jain et al. (2022): Introduces a deep learning-based approach for classifying mango leaf diseases, emphasizing the importance of early detection. Customizes SVM for feature extraction, achieving an accuracy of 97.7%.

Suwit Wongsila et al. (2021): Develops an algorithm for detecting mangoes infected with anthracnose using a deep learning system based on Convolution Neural Network (CNN). Achieves over 70% accuracy in isolating diseased mangoes.

Wenjie Zhang (2022): Addresses environmental noise challenges in mango leaf disease detection using an adversarial denoising autoencoder (ADAE) model. Compares the proposed ADAE with traditional machine learning algorithms, demonstrating superior results.

Devdutt Baresary et al. (2021): Presents a hybrid DL model combining CNN and SVM for classifying mango leaf spot disease. Attains an overall accuracy of 95.68% and demonstrates generalizability on an independent dataset.
Aayush Sharma et al. (2022): looks at how reinforcement learning algorithms can be used to make new pictures of sick and healthy mango leaves. Compares the performance of Wasserstein GAN, DCGAN, and GAN for dataset augmentation.
K Lisha Kamala et al. (2021): Emphasizes the importance of disease detection in hydroponically cultivated apples using image processing and ML techniques.
Xin Li et al. (2020): Models of convolutional neural networks Researchers in this study use SVM, ResNet, and VGG to look into how to identify and group apple leaf illnesses. ResNet-18 achieves an accuracy rate of 98.5%.
Umang Garg et al. (2021): Highlights the economic significance of the apple industry in Kashmir and proposes ML and DL for early detection of apple plant diseases.
P Nagaraj et al. (2022): Uses CNN algorithm with Inception architecture for recognizing papaya infections, achieving approximately 97% accuracy.
Priyanka Sahu et al. (2022): Conducts a systematic literature review on ML techniques in banana plant disease identification, addressing various issues such as disease classification and chilling injuries detection.

Advancing with Deep Learning

In deep learning, computers learn to classify things and make predictions based on the data they are given. Building deep learning

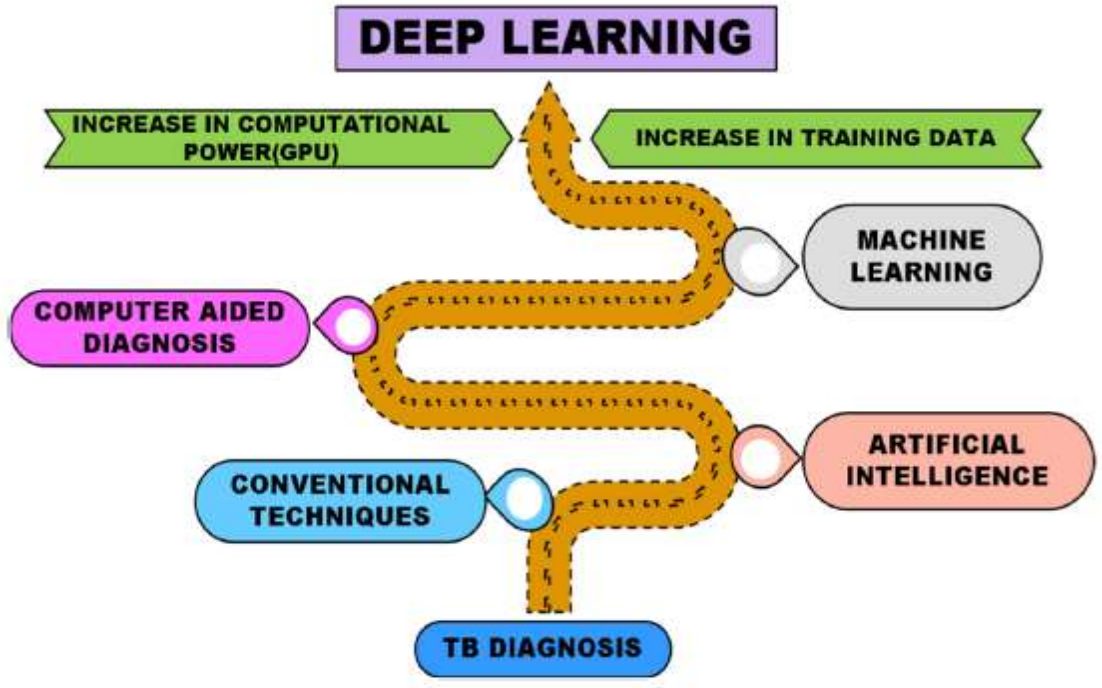

Fig.4 Evolution of artificial intelligence in TB diagnosis.

Models with high accuracy requires a combination of signals with different weights (where the dataset can be adjusted according to weights to give an expected response for a given input), which takes the data and sends them deeper and deeper into the framework of a multi-layer neural network until they reach an output layer. This strategy's multiple learnable stages make it a more effective tool for dealing with difficult challenges. “Deep” here refers to the number of hidden layers in the network, i.e., It can store a lot of knowledge hidden inside its layers, which is different from regular neural networks. Deep learning has been used a lot in

both bioinformatics and computational biology. Models that use traditional methods to machine learning have become more complex as the amount of training data and processing power have grown. (Figure 4).

Convolutional Neural Networks (CNN)

Through feed-forward artificial neural networks, CNN is a deep learning method that looks at pictures. Scientists think it is the most advanced way to sort pictures right now because the connections between its neurons are set up in a way that lets them react to the overlapping areas that make up the visual field. The pooling layer and the fully linked (FC) layers are the two most important of the many hidden layers that make it up. After the final output layer, which is where the picture classification process starts, it is normal to add FC layers. Because it doesn't change the depth, the pooling layer reduces the image's size. Based on biological processes and forms of multi-layer neural networks that were meant to use as little pre-processing as possible, CNN was created. Plus, it can learn and extract useful features by dividing the target classes while the training phase is going on since it doesn't need any previous domain knowledge. (Figure 5).

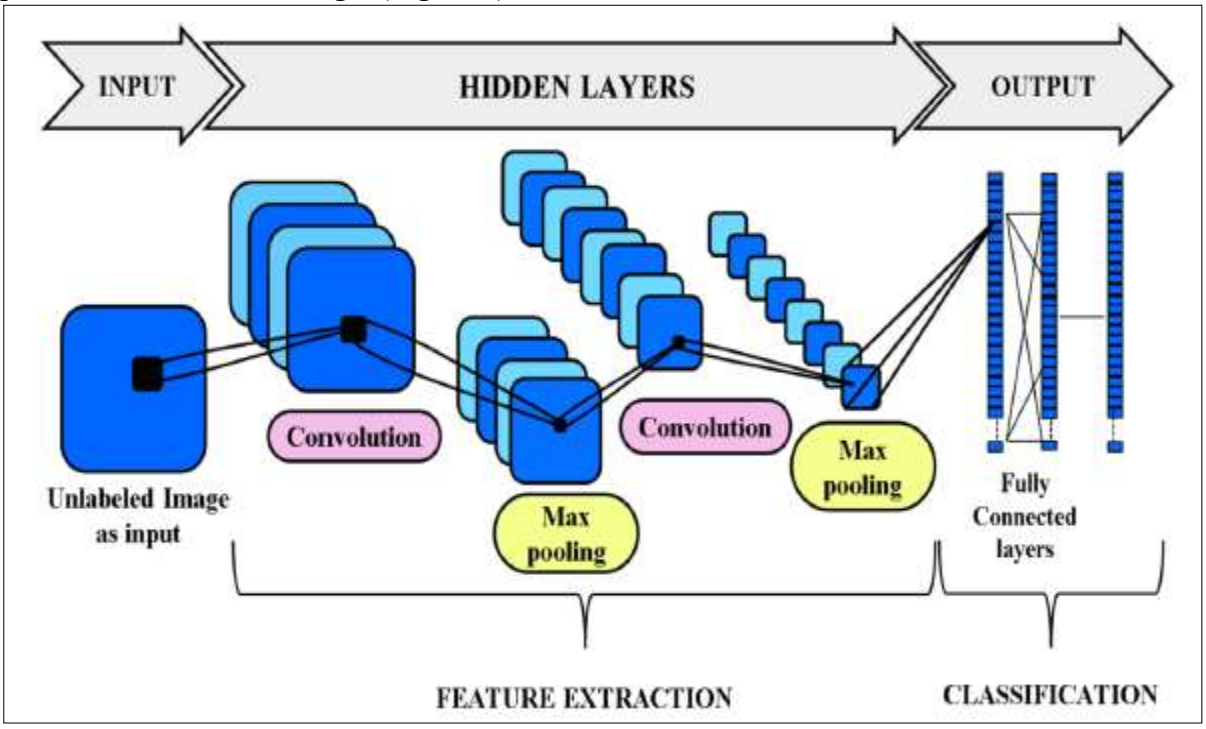

Fig.5. Working on a basic CNN model.

Does CNN Make Our Job Easier in TB Diagnosis?

CNN's shows are a unique mix of math, biology, and computer science. There are big steps forward in both picture processing and machine vision because of this. CNN is based on the idea that data (pictures) can be put into different groups in a way that is similar to how the brain does it. When a person looks at a picture, for example, they can put it into a lot of different groups based on what makes that image unique. For the same reason, the computer programme might organize the picture by first finding low-level features like edges and curves, and then using a group of hidden layers (the convolution layer, the pooling layer, and the fully connected layer) to add higher-level features on top of those ideas. So, the computer can arrange the picture in a way that makes more sense. This is how the programme can arrange the picture. This is done by breaking the picture up into several levels, with a different set of low-level traits on each level. The same thing happens with CNN models.

ISSN PRINT 2319 1775 Online 2320 7876
 UGC CARE Listed (Group -I) Journal Volume 11, Iss 11, 2022

They learn unique features from the TB dataset and then try to decide whether a new picture is of a TB case or not.Here is an explanation of the different steps that need to be taken to build a CNN model that can use chest X-rays to identify tuberculosis.

Input for a convolution layer: The images that are used to train the CNN model are its sources.

When the pictures are the right size, they are shrunk down and then moved to the hidden layers. Kernels, filters, or neurons make up each hidden layer. They are placed over a part of the input picture and are scaled based on the size of the neurons. This CNN model looks at pictures by comparing them piece by piece. Each piece is called a feature. Each feature is like a tiny picture, and each neuron is a way to identify a feature. The curves in the X-ray of the chest are recognized as a feature in the picture by one of the filters. After being applied to a picture and given more time to process, this filter will find any curves that are present in it. Additionally, there will be filters that can find things in the input picture that are similar, like straight lines, curves that bend to the right or left, or straight edges. There is also a relationship between the number of filters used and the identification depth. This means that more information can be extracted from the source picture.

Activation of the convolutional layer: One feature of the input picture can be picked out by each filter. The filter searches for the mentioned feature anywhere in the picture it can find it when it processes the image. The filter can figure out which features are responsible for turning on itself as soon as it recognizes the feature. Thereafter, the filter looks for the specific feature in the picture it was given. Now it's possible to make an activation map of the filter that was applied to the picture feature. The frequency of that feature in the picture being processed can be roughly estimated by the number that the activation map of the filter gives.

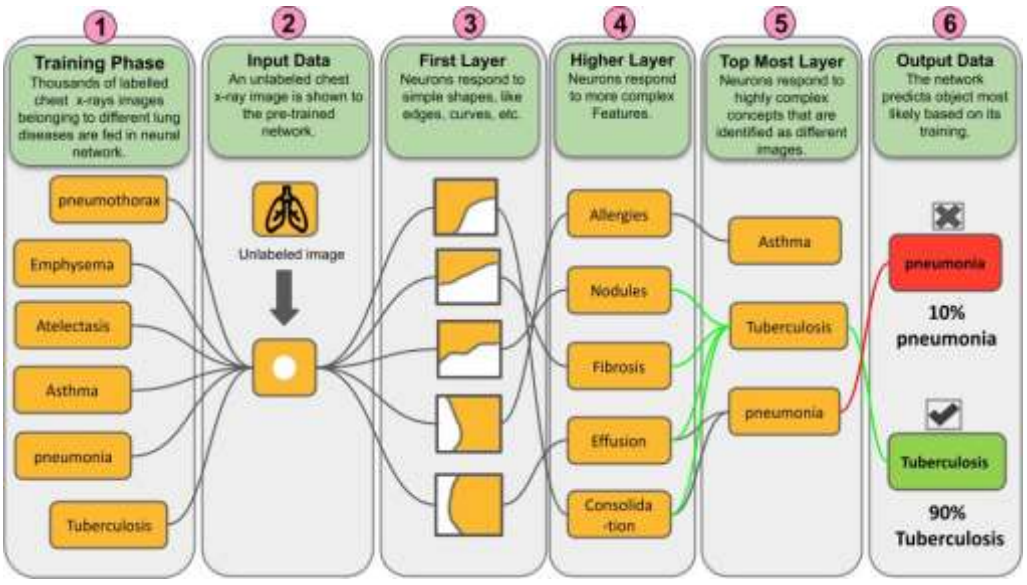

Fig.6. Representation of working of a CNN model for TB diagnosis.

As an example, let's look at a curve marker that is an 8x8 filter (Figure 6). After the picture has been processed by the filter, this filter will try to find the curves in an X-ray of the chest.

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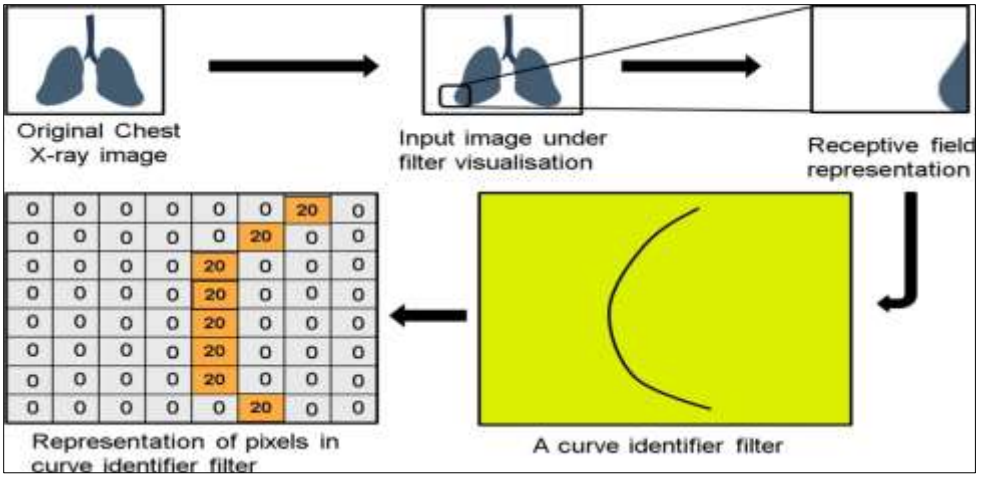

Fig. 7 Curve identifier filter and its activation for a chest X-ray image.

It will start looking for a pixel match between the input picture and its own pixels as soon as the filter figures out that a feature exists. Let's also say that a part of the picture responds to the matching process, which creates a value (the sum of the filter pixels multiplied by the input image) and an activation map. That feature is more noticeable in the picture if the activation map gives it a higher value. More specifically, it shows some kind of curve in the input image that activated the filter and vice versa. This feature's appearance is related to the value that the activation map creates. The same is true for each trait; there are multiple filters for each one. Additionally, the activation map created by the first filter is fed into the next filter, which finds another trait and creates a new activation map. By keeping looking for traits, this process will eventually lead to a more complex activation map.

IV CONCLUSIONS

In conclusion, the progress in artificial intelligence (AI) techniques, particularly deep learning (DL), has significantly advanced tuberculosis (TB) diagnosis. Supported by enhanced hardware storage and big data, AI applications have gained broader acceptance and hold promise in disease diagnosis. Notably, machine learning, especially DL models, has demonstrated success in surpassing human expertise, making it a powerful tool for TB diagnostics. Several examples showcase the successful integration of AI in TB diagnosis, particularly in early disease detection and assessing drug resistance. Instances such as the Image CLEF competition highlight the effectiveness of deep learning classifiers in identifying specific types of TB based on CT scans, achieving notable accuracy. Despite these successes, challenges persist, with data quality being a paramount concern. Acquiring reliable and sufficient data for building high-quality datasets remains a hurdle. Experimental conditions, varied symptoms, and drug resistance contribute to the complexity of generating datasets with consistent and accurate information. Efforts have been made to address these challenges, including the development of algorithms capable of handling diverse or insufficient datasets. Additionally, the integration of deep learning methods with neurofuzzy, genetic algorithms, and artificial immune systems shows promise in enhancing sensitivity, specificity, and accuracy in TB diagnosis. Limitations such as overfitting and understanding the internal mechanisms of DL models remain, primarily due to the limited availability of accurate TB diagnosis datasets. However, ongoing research in DL and integrated systems aims to overcome these limitations. Advancements in technology, including visualization

methods, contribute to better interpreting DL model decision-making processes. These techniques enhance model transparency, providing visual representations of decision rationales and increasing confidence in the model's outputs.

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