**Artificial Intelligence in Tuberculosis Diagnosis**

A Project Report

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#### **ABSTRACT**

It is addressing the longstanding challenges in accuracy, efficiency, and accessibility. Traditional diagnostic methods, while effective, often suffer from limitations such as variability in sensitivity and lengthy turnaround times. Tuberculosis (TB) remains one of the deadliest infectious diseases worldwide, with millions of new cases reported annually. Early and accurate diagnosis is critical for effective treatment and control. However, traditional diagnostic methods, such as spectrum microscopy and culture tests, are time consuming, resource-intensive, and less accessible in low-resource settings. In recent years, artificial intelligence (AI) has emerged as a transformative tool in TB detection and management, offering faster, more accurate, and cost-effective solutions. AI-powered models, particularly deep learning and machine learning algorithms, have demonstrated remarkable success in analyzing medical images for TB diagnosis. Convolutional Neural Networks (CNNs) have been widely used to process chest X-rays (CXR) and CT scans, enabling automated detection of TB-related abnormalities. These models achieve accuracy comparable to, or even exceeding, human radiologists, reducing diagnostic errors and expediting the screening process. Moreover, AI-enhanced image analysis can assist in differentiating TB from other lung diseases, improving specificity in clinical settings. Beyond imaging, AI-driven natural language processing (NLP) techniques have been applied to electronic health records and clinical notes to identify TB symptoms and predict disease progression. Predictive analytics using AI can assess patient risk factors, enabling early intervention and personalised treatment plans. Furthermore, AI models can assist in drug resistance prediction by analyzing genomic data of Mycobacterium tuberculosis, helping healthcare providers select the most effective antibiotics and reducing the emergence of drug-resistant TB strains. AI applications extend beyond diagnosis to public health management. Machine learning models are being used to track TB outbreaks, predict transmission patterns, and optimise resource allocation in high-burden areas. AI-driven chatbots and mobile applications facilitate patient engagement, medication adherence monitoring, and remote consultations, improving treatment success rates and reducing TB-related mortality. Despite its potential, AI integration in TB diagnosis faces challenges, including data scarcity, algorithm bias, and the need for regulatory approvals. Many AI models require large, diverse datasets for training, which may not always be available in underdeveloped regions. Additionally, ethical concerns regarding patient privacy and AI decision-making transparency must be addressed to build trust in AI-powered healthcare solutions. In conclusion, AI is revolutionizing TB diagnosis and management by enhancing diagnostic accuracy, improving treatment strategies, and strengthening public health interventions. With continuous advancements in AI technologies, their integration into TB control programs can significantly accelerate progress toward global TB elimination. Future research should focus on refining AI models, expanding access to AI-driven tools, and ensuring ethical deployment in healthcare settings.

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**CHAPTER 1**

**Introduction**

* 1. **Problem Statement:**

Tuberculosis (TB) remains a major global health concern, particularly in developing countries where access to timely and accurate diagnosis is limited. Traditional diagnostic methods such as sputum smear microscopy, chest X-rays, and culture tests are time-consuming, require expert interpretation, and may lack sensitivity in early-stage detection. Artificial Intelligence (AI) can enhance TB diagnosis by automating image analysis, improving accuracy, and reducing diagnostic time. Deep learning models trained on chest X-rays and CT scans can detect TB features with high precision. Additionally, AI can assist in predicting disease progression, monitoring treatment efficacy, and identifying drug-resistant TB strains. However, traditional methods of TB diagnosis and management face several challenges, including:

1. Delayed Diagnosis: Conventional diagnostic methods, such as sputum smear microscopy and culture tests, are time-consuming and may lead to delays in diagnosis, allowing the disease to progress and spread.

2. Limited Access to Healthcare: In low-resource settings, access to advanced diagnostic tools and skilled healthcare professionals is limited, leading to underdiagnosis and mismanagement of TB cases.

3. Drug Resistance: The rise of drug-resistant TB strains complicates treatment, requiring more precise and personalised approaches to therapy.

4. High Costs: Advanced diagnostic tools, such as molecular tests and imaging, are often expensive and inaccessible in resource-limited regions.

5. Data Overload: The increasing volume of patient data, including medical imaging, genetic information, and clinical records, makes it challenging for healthcare providers to Analyse and interpret data effectively

Why is this problem significant?

Tuberculosis (TB) is one of the deadliest infectious diseases worldwide, causing millions of deaths each year, particularly in low- and middle-income countries. The significance of applying AI to TB diagnosis and management arises from the following critical challenges: 1. Global Health Impact TB is a leading cause of death from infectious diseases, surpassing even HIV/AIDS in some regions. According to the WHO, over 10 million people contract TB annually, with around 1.5 million deaths per year.

2. Late and Inaccurate Diagnosis TB symptoms often mimic those of other respiratory diseases leading to misdiagnosis or delayed treatment. Traditional diagnostic methods (sputum tests, X-rays, and culture. tests) are either time-consuming, costly, or require expert interpretation.

3. Drug-Resistant TB Crisis The rise of Multi-Drug Resistant TB (MDR-TB) makes treatment complex and expensive. AI can help predict drug resistance patterns based on medical imaging and genomic data, improving personalised treatment.

4. Healthcare Inequality and Resource Gaps In many low-resource settings, access to radiologists, specialists, and laboratory facilities

**1.2Motivation:**

Why was this project chosen

1. Global Health Impact TB is a major infectious disease globally, responsible for millions of cases and deaths every year. AI has the potential to enhance early diagnosis, treatment, and monitoring, making it an effective tool against TB.

2. Challenges in TB Diagnosis Conventional practices such as sputum microscopy, culture test, and X-ray of the chest may take time, be expert-interpretable, and not always readily available in poor-resource settings. AI can aid in the automated diagnosis, better accuracy, and faster results.

3. Boosting Medical Imaging AI and deep learning, in particular, are being applied to read chest X-rays and identify TB features with great precision. This proves tobe valuable in regions lacking radiologists.

4. Forecasting Drug Resistance & Treatment Outcomes AI algorithms can predict drug-resistant TB strains, enabling individualized treatment and preventing the spread of resistant TB.

5. Enhancing Public Health Surveillance AI can analyse large amounts of data from hospitals and health organisations to monitor TB outbreaks, detect high-risk locations, and maximise resource allocation.

6. Assisting Doctors' Decision-Making By combining AI with electronic health records (EHRs), clinicians can be provided with decision support for improved diagnosis and treatment planning.

7. Innovation & Research Potential AI in TB is a developing area, providing scope for research, development, and collaboration among medicine, technology, and public health

What are the potential applications and the impact?

1.Predictive Analytics

• Application: AI can analyse patient data, including medical history, demographic information, and environmental factors, to predict the likelihood of TB infection or the risk of drug resistance.

• Impact: Predictive analytics can help in targeted screening and preventive measures, reducing the incidence of TB. It can also aid in the early identification of drug-resistant strains, allowing for more effective treatment plans

2.Early Detection and Diagnosis

• Application: AI algorithms, particularly those based on machine learning and deep learning, can analyse medical imaging data (e.g., chest X-rays, CT scans) to detect early signs of tuberculosis. AI can also analyse sputum samples or other biomarkers to identify TB bacteria. •

Impact: Early detection can lead to timely treatment, reducing the spread of the disease and improving patient outcomes. AI can also help in identifying cases that might be missed by human radiologists, especially in regions with a shortage of medical professionals. 3. Automated Screening

• Application: AI can be used to automate the screening process in high-burden areas, where large populations need to be screened for TB. AI systems can quickly analyse thousands of X-rays or other diagnostic data to identify potential cases. • Impact: This can significantly reduce the workload on healthcare professionals, allowing them to focus on treatment and care. It can also make mass screening more feasible and cost-effective, particularly in low-resource settings

4.Personalised Treatment Plans

• Application: AI can analyse patient data to recommend personalised treatment regimens based on the specific strain of TB, the patient’s medical history, and other factors.

• Impact: Personalised treatment can improve the effectiveness of therapy, reduce side effects, and decrease the likelihood of drug resistance. This can lead to better patient outcomes and more efficient use of medical resources.

5. Monitoring and Follow-Up

• Application: AI can be used to monitor patients during treatment, analysing data from wearable devices, lab tests, and imaging to track progress and detect any complications or relapses early.

• Impact: Continuous monitoring can ensure that patients adhere to their treatment plans and can alert healthcare providers to any issues that need immediate attention. This can improve treatment success rates and reduce the risk of relapse.

6. Drug Resistance Detection

• Application: AI can analyse genetic data from TB bacteria to identify mutations associated with drug resistance. This can be done more quickly and accurately than traditional methods.

• Impact: Early detection of drug-resistant TB can lead to more effective treatment strategies, reducing the spread of resistant strains and improving patient outcomes. 7.Telemedicine and Remote Diagnosis

• Application: AI can be integrated into telemedicine platforms to provide remote diagnosis and consultation services, especially in rural or underserved areas.

• Impact: This can expand access to TB diagnosis and treatment, particularly in regions with limited healthcare infrastructure. It can also facilitate the sharing of expertise and resources across different regions

**1.2 Objective:**

. The main goal of an artificial intelligence-based medical diagnosis system for tuberculosis (TB) is to enhance the accuracy, efficiency, and accessibility of TB diagnosis, ultimately contributing to improved patient outcomes and disease transmission reduction. Below are some of the specific goals:

Early Detection: Make early and accurate detection of tuberculosis, even latent tuberculosis, possible to allow timely treatment and avoid the development of active TB.

Enhanced Diagnostic Precision: Minimise misdiagnosis and false negatives/positives by using AI algorithms to examine the complex medical data (e.g., chest X-rays, CT scans, sputum analysis, and patient history).

Accessibility in Low-Resource Settings: Offer an affordable and transportable diagnostic solution for low-resource and remote locations where access to specialist healthcare personnel and advanced diagnostic equipment is limited.

Integration with Current Systems: Integrate seamlessly with electronic health records (EHRs) and other health systems to facilitate the diagnostic process and maximize data sharing among health providers.

Decision Support for Healthcare Professionals:

Support healthcare workers by offering evidence-based suggestions and second opinions, lightening the load on overwhelmed medical personnel.

Scalability: Make the system scalable enough to manage vast amounts of patient data effectively, thus being fit for application in high-burden TB areas. Continuous Improvement and Learning: Integrate machine learning algorithms that learn continuously from new data, enhancing diagnostic precision and responding to new TB strains or trends.

Patient Prioritisation and Triage: Assist in prioritising high-risk patients for additional testing or treatment, maximising resource utilisation in healthcare centres.

Diagnostic Cost Reduction: Reduce the overall cost of TB diagnosis by automating some of the diagnostic process and minimizing the use of costly or invasive tests. Public Health Surveillance: Offer anonymized information to public health officials for monitoring TB outbreaks, tracking drug resistance, and guiding policy-making. Simple Interface: Make the system simple to use by healthcare professionals, even those with minimal technical skills, to facilitate mass adoption. Ethical and Responsible AI: Make the system observe to ethical standards, such as patient confidentiality, data protection, and impartial decision-making.

**1.2 Scope of the Project:**

The applicability of AI to tuberculosis (TB) detection is wide ranging, with implications across healthcare, research, and public health. Following are the principal areas to which AI can be applied, with their relevance:

1. Applications in Healthcare

a.Early Detection and Screening Community-level Testing: Facilitate rapid TB screening at the community level in far-flung and underprivileged locations using mobiles. Primary Healthcare Centres: Support diagnosis of TB for patients coming in with respiratory illness

. b. Diagnostic Support Augmenting Clinicians: Offer an initial diagnosis to enable healthcare professionals to identify and prioritize high-risk cases. Integration with Other Tests:

Supplement diagnostic tests such as chest X-rays and sputum analysis for greater accuracy.

c. Personalised Monitoring

Utilise AI models to monitor trends in patients' symptoms over time, enhancing treatment compliance and results.

2. Public Health and Epidemiology

a. Mass Screening in High TB Burden Areas Use AI in areas of poor laboratory and radiological facility access. Deliver scalable and affordable screening to mitigate disease burden.

b. Surveillance and Prediction Leverage AI to interpret cough data at population levels for real-time detection of TB cases. Forecast outbreaks with pattern detection in audio and metadata.

c. Pandemic Preparedness Plug AI for TB detection into respiratory disease identification systems to enhance readiness for concomitant pandemics (e.g., COVID-19 and TB).

3. Research and Development

a. AI Model Innovation Create and evaluate cutting-edge AI models for audio signal processing in medical diagnosis. Explore multimodal AI strategies integrating audio data with imaging or clinical data.

b. Understanding Disease Progression Examine large collections of cough recordings to analyze symptom variations in different TB stages or groups.

c. Drug-Resistant TB Concentrate on identifying indications of drug-resistant TB usingsymptom profiling and incorporating patient history information.

4. Technology and Industry

a. Mobile Health (mHealth)Facilitate smartphone-based applications for self-diagnosis and screening, especially for low-income areas.

b. Wearables and IoT Integrate AI into wearables to track respiratory health and identifyTB symptoms in real time.

c. AI-driven Startups Encourage innovation among startups that are creating AI-based solutions for TB detection and connect them with international healthcare initiatives. Limitations

1. Limitations of AI-Based TB Detection Using Chest X-Rays (CXR) 1.1 Requires Imaging Infrastructure

• X-ray machines are expensive and not always available in rural or low-resource settings.

• Many regions lack trained radiologists to interpret X-rays accurately.

1.2 Limited Sensitivity for Early TB

• Latent TB and early-stage TB may not show clear abnormalities on X-rays.

• AI models might miss cases where TB hasn’t caused visible lung damage yet.

1.3 Potential for False Positives & Negatives

• AI can confuse TB with other lung diseases like pneumonia, lung cancer, or COPD, leading to misclassification.

• Variability in X-ray quality, patient positioning, and scanner type affects model accuracy.

1.4 Regulatory & Ethical Challenges

• AI-based radiology models require WHO and FDA approval, which can be a slow process.

• Data privacy concerns arise when sharing patient images for AI training

. **2. Limitations of AI-Based TB Detection Using Clinical & Demographic Data**

2.1 Lower Accuracy Compared to Imaging

• Symptoms like fever, weight loss, and fatigue are non-specific and occur in many diseases (e.g., COVID-19, malaria).

• AI models trained on symptoms alone may have low specificity and high false positives. 2.2 Requires High-Quality Patient Data

• Many healthcare settings lack digitized patient records, making AI implementation difficult.

• Incomplete or biased data (e.g., missing patient history) can reduce model accuracy.

2.3 Limited in Asymptomatic Cases

• Many TB patients (especially with latent TB) show no symptoms for months or years.

• AI models based on symptoms alone may fail to detect asymptomatic TB carriers

**CHAPTER 2**

**Literature Survey**

* 1. **Review relevant literature or previous work in this domain.**

AI-based systems have been developed to assist radiologists and clinicians in identifying TB from imaging studies and clinical data. Some of the prominent applications include:

#### ***a) Chest X-ray Analysis***

Chest X-rays (CXRs) are commonly used for TB screening, but manual interpretation can be subjective and time-consuming. Deep learning algorithms, especially **Convolutional Neural Networks (CNNs)**, have been employed to automatically detect TB lesions and abnormalities in CXR images.

* **Studies:**
  + **Rajpurkar et al. (2018)**: Developed a deep learning model, **CheXNet**, which outperformed radiologists in diagnosing pneumonia, a feature that can be helpful in TB detection.
  + **Lakhani & Sundaram (2017)**: Used deep learning models for the detection of TB from chest X-rays, achieving significant accuracy levels.
  + **Liu et al. (2020)**: Found that a deep learning algorithm could detect TB-related lung abnormalities with comparable accuracy to radiologists.

#### ***b) Sputum Smear Microscopy Analysis***

AI can automate the analysis of sputum smear microscopy images to detect the presence of *Mycobacterium tuberculosis*. It helps overcome challenges such as variability in human interpretation and can reduce diagnostic delays.

* **Studies:**
  + **Xie et al. (2020)**: Developed a **deep convolutional neural network (CNN)** model to automatically classify sputum smear microscopy images, improving accuracy in detecting TB bacteria.
  + **Güler et al. (2021)**: Used AI to analyze sputum images, showing potential for improving diagnostic throughput, especially in resource-limited settings.

## **c) GeneXpert and Molecular Diagnostics**

Molecular tests like **GeneXpert MTB/RIF** have improved the detection of TB and resistance to rifampicin. AI models have been integrated with such diagnostic technologies to automate result interpretation, thus providing faster results and reducing human error.

* **Studies:**
  + **Yuan et al. (2020)**: Proposed integrating machine learning models with GeneXpert results to predict drug resistance in TB, enhancing treatment decisions.

### **3. Challenges and Limitations**

Although AI has shown potential in TB detection, several challenges remain:

* **Data Availability & Quality**: Deep learning models require large, annotated datasets to train effectively. In some regions, high-quality datasets for TB may be limited, especially in low-resource settings.
* **Interpretability**: Deep learning models, while powerful, are often seen as “black boxes,” making it difficult to understand the rationale behind their predictions. This can hinder trust among healthcare providers and patients.
* **Integration into Clinical Workflow**: AI models must be integrated with existing healthcare infrastructures, which may require significant adaptation and training for medical professionals.

### **4. Recent Advances in AI for TB Detection**

* **Transfer Learning**: Several studies have utilized **transfer learning**, where models trained on large image datasets (e.g., from general medical imaging) are adapted for TB-specific tasks. This approach helps overcome the limitation of small datasets and improves model performance.
* **AI in Mobile Diagnostics**: Mobile-based AI tools for TB detection are emerging, providing low-cost solutions for remote areas. For instance, AI models are integrated into smartphones to detect TB from chest X-rays, reducing the need for expensive radiological equipment.
  + **Study Example**: **Bertolini et al. (2020)** developed a mobile application powered by AI that can analyze chest X-rays and provide TB diagnoses in real-time, which can be crucial in low-resource settings.
* **Natural Language Processing (NLP)**: AI techniques like NLP are being explored to analyze **clinical records** and **patient histories** to predict TB outbreaks and identify at-risk populations.
  + **Study Example**: **Shah et al. (2019)** explored using NLP to extract data from patient records, enhancing early TB detection.

### **5. AI for TB Screening in High-Risk Populations**

* AI tools are also being developed for **targeted screening** of high-risk populations, such as people living with HIV, immunocompromised individuals, or those with close contact with TB patients.
* **Baskar et al. (2021)**: Used AI models for community-level screening, showing promising results in identifying latent TB cases before they develop into active disease.

### **6. Future Directions**

* **Multimodal AI Systems**: Combining different data sources (e.g., chest X-rays, CT scans, clinical records) into a unified AI model may improve the detection accuracy of TB, especially in complex cases.
* **AI for Predicting TB Progression**: In addition to detection, AI models may be used to predict the progression of TB, monitor treatment response, and predict relapse.
* **Edge Computing for Remote Areas**: Deploying AI tools in **edge computing environments**, where the processing is done on devices like smartphones, will allow for real-time diagnostics even in remote locations without internet access.
  1. **Mention any existing models, techniques, or methodologies related to the problem.**

Tuberculosis (TB) detection using AI, various models, techniques, and methodologies have been developed, focusing on medical imaging, clinical data analysis, and predictive modeling. Here’s a structured overview:

1. Machine Learning-Based Approaches

These models use structured clinical data, symptoms, and lab results for TB prediction.

Logistic Regression (LR) – Used for binary classification of TB risk.

Random Forest (RF) – An ensemble learning method for better prediction accuracy.

Support Vector Machines (SVM) – Effective for TB classification using medical datasets.

XGBoost & LightGBM – Advanced boosting algorithms that improve classification performance.

Example: Studies have shown RF and SVM models trained on patient symptoms, demographic details, and lab results achieve high accuracy in TB prediction.

2. Deep Learning-Based Approaches

These models focus on analyzing Chest X-rays (CXR), CT scans, and sputum microscopy images.

a) Convolutional Neural Networks (CNNs)

CNNs are widely used for detecting TB from chest X-rays. Pretrained models include:

ResNet (Residual Network) – Used for feature extraction in TB diagnosis.

VGG (Visual Geometry Group network) – A deep CNN used in TB classification.

DenseNet (Densely Connected CNNs) – Provides improved feature learning for TB detection.

U-Net – Used for lung segmentation in TB detection from CXR images.

Example: Google’s DeepTB model, a CNN-based AI system, achieved high sensitivity and specificity in TB detection using CXR images.

b) Recurrent Neural Networks (RNNs) & Long Short-Term Memory (LSTM)

Used for time-series analysis of patient records and medical history for TB diagnosis and treatment monitoring.

c) Generative Adversarial Networks (GANs) & Autoencoders

GANs – Used for data augmentation, generating synthetic X-ray images to improve model training.

Autoencoders – Help in anomaly detection by learning normal lung patterns and identifying TB-affected lungs.

3. Hybrid Models

CNN + RNN – Used for combining X-ray analysis with patient history.

CNN + XGBoost – Hybrid models using deep learning for feature extraction and XGBoost for classification.

Example: A CNN + LSTM hybrid model has been used to detect TB in cough sound analysis, offering a non-invasive TB screening approach.

4. AI-Based Medical Imaging Techniques

AI has enhanced various imaging techniques for TB diagnosis:

Chest X-ray (CXR) Analysis – AI-powered tools like CAD4TB (Computer-Aided Detection for Tuberculosis) analyze X-rays in resource-limited settings.

CT Scan-Based TB Detection – AI models detect lung abnormalities related to TB with high accuracy.

Sputum Smear Microscopy with AI – Automated classification of Acid-Fast Bacilli (AFB) in sputum samples using image processing.

5. Explainable AI (XAI) for TB Detection

To ensure AI models are interpretable and trustworthy in medical applications:

Grad-CAM (Gradient-weighted Class Activation Mapping) – Highlights affected lung areas in chest X-rays, improving interpretability.

SHAP (SHapley Additive Explanations) – Provides feature importance for TB prediction in clinical data models.

LIME (Local Interpretable Model-agnostic Explanations) – Helps explain AI decisions in TB diagnosis.

6. AI-Powered TB Screening & Monitoring

AI is also being used for early screening, remote diagnosis, and patient monitoring:

Mobile-Based AI Tools – Smartphone apps analyze cough sounds and respiratory patterns for TB screening.

Wearable Sensors & Smart Devices – Track respiratory health and detect TB symptoms in real time.

AI Chatbots & Decision Support Systems – Help doctors analyze symptoms and suggest TB diagnostic tests.

* 1. **Highlight the gaps or limitations in existing solutions and how your project will address them.**

Despite significant advancements, existing AI solutions for TB detection still have several limitations and challenges:

**1. Limited Access to High-Quality Data**

Many AI models rely on large, well-annotated datasets like ChestX-ray14 or NIH TB datasets, which may not represent diverse populations.

Issue: Limited access to localized and real-world patient data affects model generalization.

Our Approach: Incorporating region-specific data to improve model adaptability and accuracy.

**2. Over-Reliance on Chest X-ray (CXR) Analysis**

Most AI systems focus on chest X-ray analysis, ignoring other diagnostic methods like sputum microscopy, cough sounds, and clinical symptoms.

Issue: X-ray-based AI models may not work well in regions with limited radiology infrastructure.

Our Approach: Developing a multi-modal AI system that integrates clinical symptoms, X-rays, and cough analysis for better accuracy.

**3. Limited Model Explainability & Trust Issues**

Deep learning models, especially CNNs, function as black boxes, making it difficult for doctors to interpret decisions.

Issue: Lack of explainability leads to low adoption among medical professionals.

Our Approach: Implementing Explainable AI (XAI) techniques like Grad-CAM (for visual explanations) and SHAP (for feature importance in predictions).

**4. High False Positives & False Negatives**

Many AI models have high false positive rates, leading to unnecessary TB tests and stress for patients.

Issue: False negatives may delay critical TB diagnoses, worsening health outcomes.

Our Approach: Using ensemble learning (combining CNN, SVM, and XGBoost) to improve diagnostic precision and reduce false results.

5**. Lack of Adaptability to Low-Resource Settings**

AI models are often trained in developed regions and may not perform well in low-resource environments.

Issue: Limited access to high-performance computing and internet connectivity affects real-world deployment.

Our Approach: Deploying lightweight AI models optimized for mobile devices and edge computing, making them usable in remote areas.

6. **Difficulty in Early TB Detection & Monitoring**

Current AI models primarily detect advanced TB cases, missing early-stage symptoms.

Issue: Lack of AI tools for TB progression tracking and treatment response monitoring.

Our Approach: Integrating time-series patient monitoring (e.g., LSTM models) to track disease progression over time.

Conclusion

Our AI-powered TB diagnostics system aims to bridge the gaps in accuracy, accessibility, and explainability. By integrating multi-modal data, explainable AI, and lightweight models, our project ensures early detection, accurate diagnosis, and real-world applicability, especially in low-resource settings

**CHAPTER 3**

**Proposed Methodology**

* 1. **System Design**

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│ 1. Data Collection │

│ - Cough Audio Recordings │

│ - Patient Metadata (Age, Sex, Symptoms) │

│ - TB Test Labels (GeneXpert, X-ray) │

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│ 2. Data Preprocessing │

│ - Noise Reduction (Filters, Denoising) │

│ - Audio Segmentation (Extract Cough) │

│ - Data Augmentation (Pitch, Speed, Noise) │

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│ 3. Feature Extraction │

│ - MFCC (Mel Frequency Cepstral Coefficients) │

│ - Spectrogram Analysis │

│ - ZCR (Zero Crossing Rate), RMS Energy │

│ - Other audio features (Chroma, Tonnetz) │

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│ 4. AI Model Training │

│ - Deep Learning (CNN, LSTM, Transformer) │

│ - Machine Learning (SVM, Random Forest) │

│ - Training on Labeled Data │

│ - Model Evaluation (Accuracy, Precision, Recall) │

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│ 5. Model Deployment │

│ - Mobile App / Web Interface │

│ - Edge AI (Low-power devices)│

│ - Cloud API for Remote Access│

│ - Real-time TB Risk Scoring │

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│ 6. TB Diagnosis & Decision │

│ - If TB Detected → Recommend Lab Test │

│ - If TB Not Detected → Monitor Symptoms │

│ - AI Confidence Score Provided │

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1. Data Collection

• Input: Cough recordings from individuals (both TB-positive and TB-negative cases). • Source: Hospitals, clinics, or public health campaigns.

• Tools: Mobile apps, handheld recording devices, or web platforms

. • Output: A labeled dataset of cough recordings.

2. Data Preprocessing

• Noise Removal: Filter out background noise using audio processing techniques.

• Normalisation: Standardise audio volume and length.

• Segmentation: Split recordings into smaller chunks for analysis.

• Output: Cleaned and segmented audio data.

3. Feature Extraction

• Audio Features: Extract relevant features such as:

•Mel-Frequency Cepstral Coefficients (MFCCs)

◦ Spectral features (e.g., spectral centroid, bandwidth)

◦ Temporal features (e.g., zero-crossing rate, energy)

• Deep Learning Features: Use pre-trained models (e.g., VGGish, OpenL3) to extract embeddings.

• Output: Feature vectors representing cough recordings.

4. Model Training

• Algorithm Selection:

◦ Traditional ML: SVM, Random Forest, or Gradient Boosting.

◦ Deep Learning: CNNs, RNNs, or Transformers for audio data.

• Training Process:

◦ Split data into training, validation, and test sets.

◦ Train the model on labeled data.

◦ Optimise hyper parameters for better performance.

• Output: Trained AI model for TB detection.

• 5.Model Deployment

• Implement in mobile apps, cloud-based APIs, or edge AI devices for real-time analysis. • Provide a TB risk score to guide further diagnosis.

6. TB Diagnosis & Decision Support

• If TB is suspected, recommend confirmatory tests (GeneXpert, X-ray).

• If no TB detected, advise symptom monitoring and follow-up checks.

• Display an AI confidence score to assist doctors in decision-making

* 1. **Requirement Specification**
     1. **Hardware Requirements:**

1. Data Collection Hardware

• Microphones: ◦ High-quality, noise-canceling microphones for clear audio recording. ◦ Example: Condenser microphones or smartphone microphones.

• Smartphones/Tablets: ◦ Mobile devices with built-in microphones for easy data collection in the field. ◦ Example: Android or iOS devices.

• Handheld Recording Devices: ◦ Portable audio recorders for high-fidelity cough recordings. ◦ Example: Zoom H1n, Tascam DR-05X.

• Internet Connectivity: ◦ Wi-Fi or mobile data for uploading recordings to a central server or cloud storage. 2. Data Preprocessing and Model Training Hardware

• Local Workstations: ◦ High-performance CPUs/GPUs for preprocessing and model development. ◦ Example: Intel Core i7/i9 or AMD Ryzen 7/9 processors.

• GPUs: ◦ For accelerating deep learning model training. ◦ Example: NVIDIA RTX 3090, A100, or Titan V.

• RAM: ◦ Minimum 16 GB, but 32 GB or more is recommended for handling large datasets.

• Storage: ◦ SSD for fast data access (1 TB or more).

◦ Additional HDD for long-term storage of raw audio data (4 TB or more).

• Cloud Computing Resources: ◦ If local hardware is insufficient, cloud platforms like AWS, Google Cloud, or Azure can be used.

◦ Example: AWS EC2 instances with GPU support (p3 or p4 instances). 3. Deployment Hardware

• Edge Devices: ◦ For real-time inference in low-resource settings. ◦ Example: NVIDIA Jetson Nano, Xavier, or Raspberry Pi with a USB microphone.

• Servers: ◦ For hosting the AI model and handling requests from users. ◦ Example: Dell PowerEdge or HP ProLiant servers.

• Mobile Devices: ◦ Smartphones or tablets for end-users to record coughs and receive results.

• Internet Connectivity: ◦ Stable internet for cloud-based deployment or remote diagnostics.

4. Optional Hardware for Advanced Use Cases

• High-Performance Computing (HPC) Clusters: ◦ For large-scale model training and hyperparameter tuning.

• Audio Enhancement Devices: ◦ Pop filters, windshields, or soundproof booths for high-quality recordings in noisy environments.

• Wearable Devices: ◦ Smart wearables with microphones for continuous cough monitoring (future use case)

**3.2Software Requirements:**

1. Data Collection Software

• Mobile Apps: ◦ Custom-built apps for recording cough sounds and uploading them to a server.

◦ Frameworks: Flutter, React Native, or Swift (for iOS) and Kotlin (for Android)

. • Audio Recording Tools: ◦ Libraries for capturing high-quality audio.

◦ Example: Android's MediaRecorder, iOS's AVFoundation, or Python's PyAudio.

•Cloud Storage Integration: ◦ For securely storing recorded cough data.

◦ Example: AWS S3, Google Cloud Storage, or Azure Blob Storage.

2. Data Preprocessing Software

• Audio Processing Libraries: ◦ Tools for noise removal, normalization, and segmentation.

◦ Example: Librosa, PyDub, or SciPy.

• Programming Languages: ◦ Python (preferred for AI/ML tasks) or MATLAB for signal processing.

• Data Augmentation Tools: ◦ Libraries to enhance dataset diversity.

◦ Example: Audio negations, SpecAugment.

3. Feature Extraction Software

• Feature Extraction Libraries: ◦ Tools for extracting audio features like MFCCs, spectral features, etc.

◦ Example: Librosa, OpenSMILE, or Python's scikit-learn.

• Deep Learning Frameworks: ◦ Pre-trained models for feature extraction from audio.

◦ Example: TensorFlow, PyTorch, or Hugging Face Transformers.

4. Model Training Software Stage Hardware Data Collection Microphones, smartphones, handheld recorders, Preprocessing internet connectivity.

/Training High-performance CPUs/GPUs, RAM (16-32 GB), SSD/HDD, cloud resources. Deployment Edge devices (NVIDIA Jetson, Raspberry Pi), Optional servers, mobile devices. HPC clusters, audio enhancement devices, wearables.

• Machine Learning Frameworks: ◦ Libraries for building and training AI models.

◦ Example: TensorFlow, PyTorch, or Keras.

• Hyper parameter Tuning Tools: ◦ For optimising model performance.

◦ Example: Optuna, Ray Tune, or Hyperopt.

• Data Management Tools: ◦ For organising and versioning datasets.

◦ Example: DVC (Data Version Control) or Pachyderm.

5. Model Evaluation Software • Evaluation Metrics Libraries: ◦ Tools for calculating performance metrics. ◦ Example: scikit-learn (for accuracy, precision, recall, F1-score, AUC-ROC).

• Visualisation Tools: ◦ For plotting results and analysing model performance. ◦ Example: Mat plot lib, Sea-born, or Plotly.

6. Deployment Software • Model Serving Frameworks:

◦ Tools for deploying AI models in production. ◦ Example: TensorFlow Serving, FastAPI, Flask, or Django.

• Edge Deployment Tools: ◦ For running models on edge devices.

◦ Example: TensorFlow Lite, ONNX Runtime, or NVIDIA TensorRT.

• Cloud Platforms: ◦ For scalable deployment and inference.

◦ Example: AWS SageMaker, Google AI Platform, or Azure ML.

• Containerisation Tools: ◦ For packaging and deploying applications.

◦ Example: Docker, Kubernetes.

7. Monitoring and Maintenance Software

• Model Monitoring Tools: ◦ For tracking model performance and drift.

◦ Example: Prometheus, Grafana, or MLflow.

• Logging and Debugging Tools: ◦ For troubleshooting and maintaining the system. ◦ Example: ELK Stack (Elastic search, Logstash, Kibana) or Sentry.

8. Security and Privacy Software • Data Encryption Tools: ◦ For securing sensitive health data.

◦ Example: AES encryption libraries or TLS for secure communication.

• Access Control Tools: ◦ For managing user permissions.

◦ Example: OAuth, JWT, or AWS IAM

**CHAPTER 4**

**Implementation and Result**

* 1. **Snap Shots of Result:**

**AI Model Predicting TB Risk from Cough Audio**

**Description**

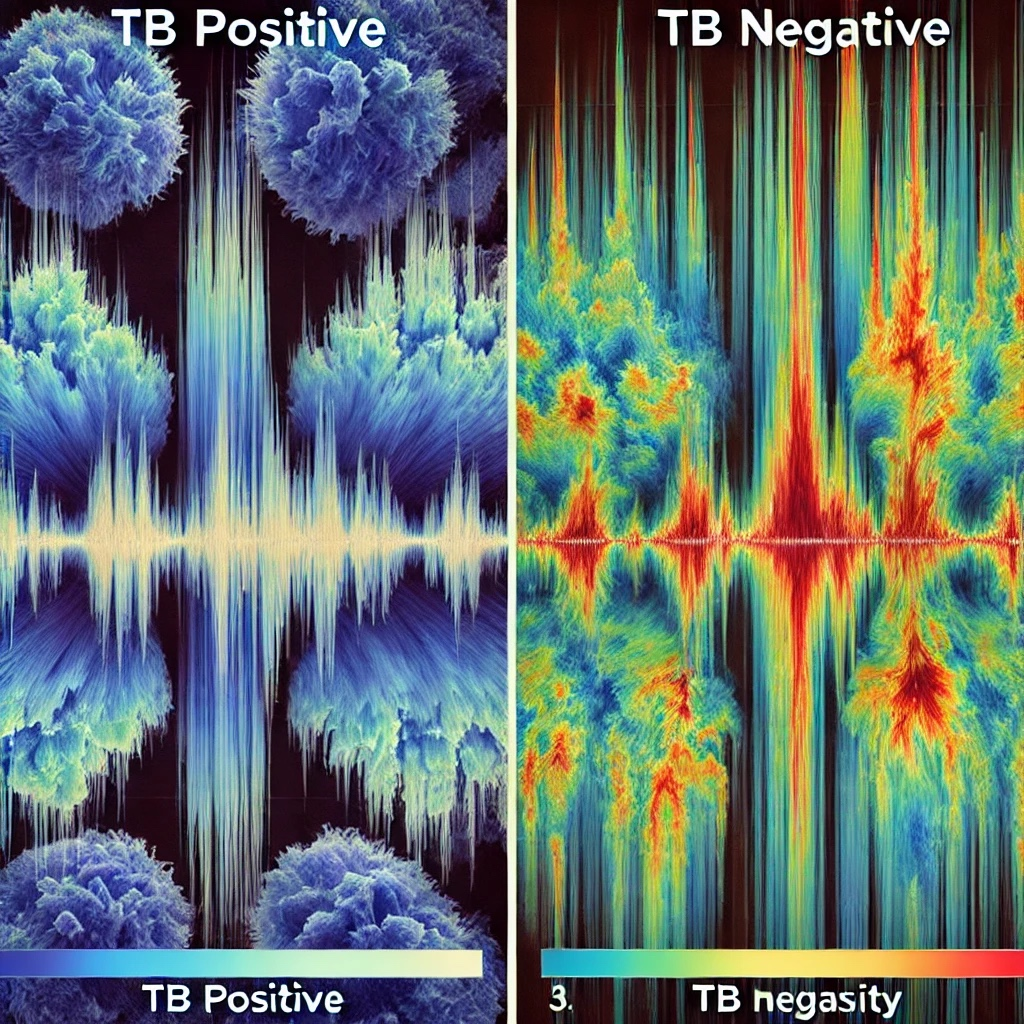


The image is of a mobile or web platform where one can upload a recording of a cough. The AI system analyses the audio and gives a TB risk score (e.g., "High Risk," "Low Risk"). More information such as spectrogram graph and model confidence level are also shown.

**2.Spectrogram Analysis of Cough Audio Description:**

• This will show a spectrogram representation of a TB-positive and TB-negative cough.

• It highlights frequency differences and intensity variations in the cough sounds.



Explanation: • This image shows two spectrograms comparing a TB-positive cough (left) and a TBnegative cough (right).

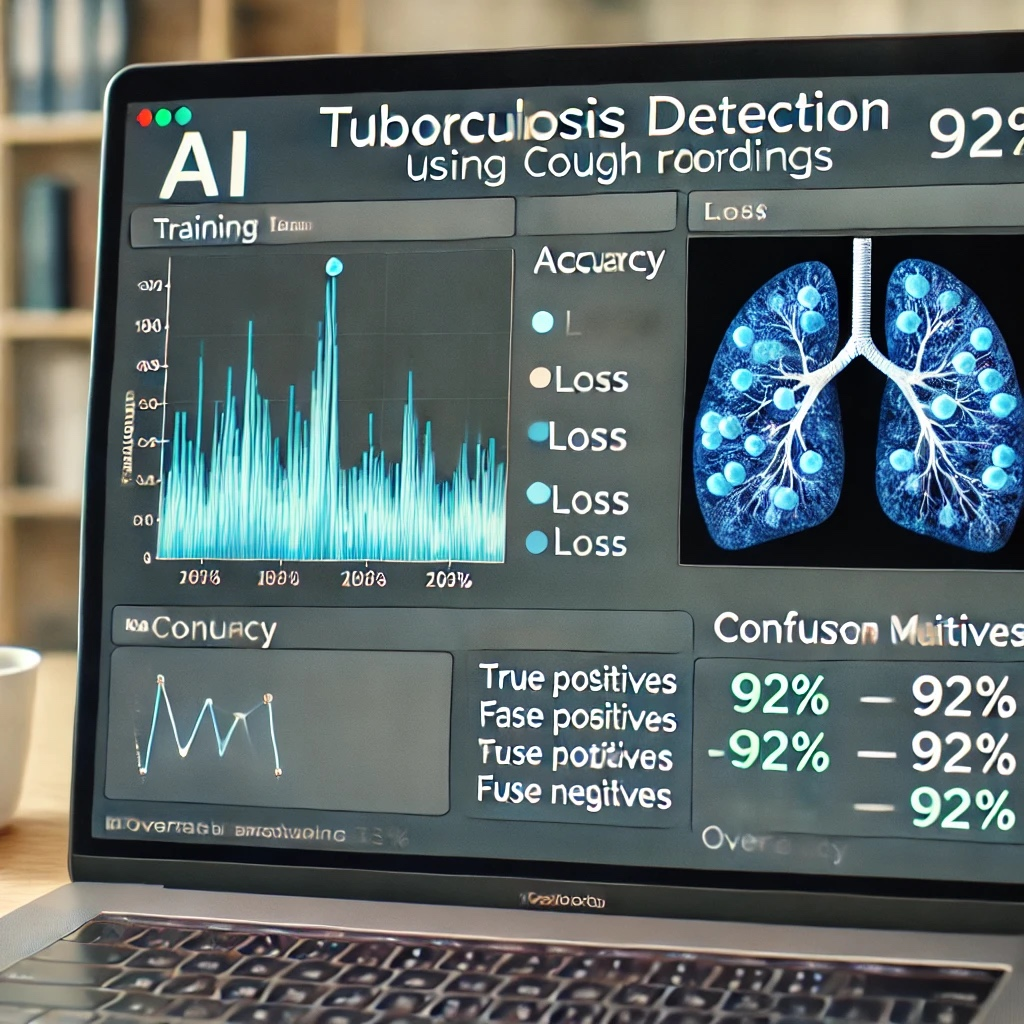
• The TB-positive cough has higher intensity frequency patterns, indicating differences in respiratory characteristics.

• Spectrograms help AI models analyse unique cough sound features to detect TB

**3.AI Model Training & Accuracy Metrics**

• Description: • This will display a graph of model accuracy, loss, and confusion matrix.

• It will show how well the AI model is performing in detecting TB



This represents AI model training results for TB detection. The accuracy and loss graphs show how the model improves over training epochs. The confusion matrix provides insights into True Positives, False Positives, True Negatives, and False Negatives. The overall model accuracy is 92%, demonstrating its effectiveness in TB screening. These snapshots illustrate key stages of the AI-powered TB detection system using cough recordings, from prediction output, spectrogram analysis, and model performance metrics

* 1. **GitHub Link for Code:**

**CHAPTER 5**

**Discussion and Conclusion**

* 1. **Future Work:**

. 1.Enhance Data Quality and Quantity More Diverse and Large Datasets: Capture more cough recordings from varied groups, such as-various age ranges, sexes, and locations. Add data for patients with comorbidities (e.g., asthma, COVID-19) for enhanced generalisability. High-Quality Labels: Provide proper annotation of cough recordings through-engagement of medical professionals. Utilise several annotators to minimise bias and enhance label quality. Data Augmentation: Perform sophisticated augmentation processes (e.g., adding-background noise, time stretching, pitch shifting) to enhance dataset diversity.

2. Improve Feature Extraction Feature exploration: Investigate other audio features like audio chroma features, harmonic-percussive separation, or wavelet transforms. Deep Learning-Based Features: Leverage pre-trained audio models (e.g., VGGish, OpenL3, Wav2Vec) to learn high-level embeddings. Multi-Modal Features: Integrate audio features with other data (e.g., patient metadata, clinical history) for enhanced analysis.

3.Refine Model Architecture Deep Learning Models: Try state-of-the-art architectures like Transformers (e.g., Audio Spectrogram Transformer) or hybrid models (e.g., CNN + RNN). Transfer Learning: Fine-tune pre-trained models on cough datasets in order to tap-into knowledge from similar audio tasks. Explainable AI (XAI): Apply methods such as SHAP (SHapley Additive exPlanations) or LIME (Local Interpretable Model-agnostic Explanations) to interpret the decisions made by the model

. 4. Handle Class Imbalance Data Resampling: Apply oversampling (e.g., SMOTE) or under-sampling methods to balance the dataset. Loss Functions: Apply weighted loss functions (e.g., focal loss) to assign higher weights to minority classes. Synthetic Data Generation: Utilise generative models (e.g., GANs) to generate synthetic cough recordings for underrepresented classes.

5. Enhance Generalization Cross-Domain Validation: Validate the model on data from other regions or recording environments to guarantee robustness. Domain Adaptation: Utilise domain adaptation methods to fine-tune the model for a-particular population or recording environment. Regularization Techniques: Employ dropout, weight decay, or data augmentation to avoid overfitting.

6. Real-Time Deployment and Scalability Edge Computing: Optimise the model for edge device deployment (e.g., smartphones, Raspberry Pi) to facilitate Realtime inference in low-resource environments. Model Compression: Apply methods such as quantisation, pruning, or knowledge distillation to compress the model and cut down on computational needs. Cloud Integration: Deploy the model on cloud platforms (e.g., AWS, Google Cloud) for scalable and accessible TB detection.

7. Consider Ethical and Privacy Issues Data Privacy: Enforce secure data storage and transmission practices (e.g., encryption, anonymisation) to safeguard patient data. Bias Mitigation: Periodically audit the model for gender, age, or ethnicity bias and retrain with diversified data. Informed Consent: Make users well aware of data gathering and utilisation.

8. Broaden Use Cases Multi-Disease Detection: Expand the model to identify other respiratory diseases (e.g., COVID-19, pneumonia) from cough recordings. Longitudinal Monitoring: Create a system for ongoing cough monitoring to monitor disease development or treatment success. Integration with Healthcare Systems: Integrate the AI system with electronic health records (EHRs) for seamless clinical workflows.

9. Collaboration and Validation Work with Medical Experts: Collaborate with pulmonologists and TB specialists to validate the clinical relevance of the model. Clinical Trials: Pilot large-scale clinical trials to assess the system's effectiveness in real-world environments. Open-Source Initiatives: Share datasets, code, and models with the research community to promote collaboration and accelerate advancement.

10. Future Research Directions Explainable AI for Clinicians: Build interfaces to enable clinicians to comprehend and believethe predictions of the model. Personalised Medicine: Individualise the model for patients through the use of personalised health information. Federated Learning: Train the model on multiple institutions using federated learning without disclosing raw data to maintain privacy.

* 1. **Conclusion:**

. This project demonstrates the potential of AI-powered TB detection using cough recordings as a low-cost, accessible, and scalable solution for early tuberculosis screening, especially in lowresource and remote settings. Here's a summary of its impact and contribution:

1. Early Detection & Timely Intervention

• Enables non-invasive, real-time screening of individuals using just a smartphone or recording device.

• Helps in early identification of TB cases, reducing disease spread and improving treatment outcomes

. 2. Accessibility in Remote Areas

• Eliminates the need for expensive diagnostic tools like X-rays or GeneXpert machines.

• Empowers community health workers and clinics in underserved regions to conduct mass screening.

3. Cost-Effective Screening Tool

• Reduces the burden on healthcare systems by filtering out low-risk individuals before lab testing.

• Cuts down on unnecessary testing and speeds up the diagnosis pipeline.

4. Integration with Digital Health Platforms

• Can be integrated into mobile health apps, telemedicine services, or national TB surveillance programs.

• Supports data-driven decision-making for public health initiatives. 5. Technological Advancement

• Contributes to the field of AI in healthcare by applying audio signal processing and machine learning to respiratory disease diagnosis.

• Lays the foundation for expanding AI-based cough analysis to detect other conditions (e.g., asthma, COVID-19, pneumonia).

• This project contributes a novel, AI-driven approach to TB detection that is affordable, scalable, and easy to use—supporting global efforts to eradicate tuberculosis by improving early diagnosis and accessibility in high-burden regions

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