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Chest X-Ray Pulmonary Tuberculosis Detection System

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Abstract: The global health problem of Tuberculosis impacts public health centers primarily in regions where resources are limited. Proficient radiologists currently play the key role in identifying Pulmonary Tuberculosis (PTB) within chest X-ray images. The proposed system implements deep learning through Convolutional Neural Networks (CNNs) to develop an automated tuberculosis detection system that delivers accurate results. The application functions as an Android program that lets users add X-ray images through an intuitive interface while it analyzes symptoms to show diagnostic assessments. For optimal patient care the system incorporates features to prevent diseases through education and it provides doctor reminder services and symptom diagnosis capabilities to support healthcare professionals. The suggested system intends to resolve time-sensitive TB diagnosis problems by providing a flexible and accessible diagnostic solution for both medical staff and patients.
Keywords: Tuberculosis Detection, Deep Learning, Convolutional Neural Networks, Android Application, Pulmonary Tuberculosis, Medical Imaging

I. INTRODUCTION

Pulmonary tuberculosis (PTB) stands as the most common manifestation of tuberculosis (TB) which ranks among the leading ten causes of death across the globe. The correct identification of diseases at an early stage remains essential for proper disease treatment methods alongside disease prevention through limiting disease transmissions. X-ray diagnostics of TB exhibit human-related errors in detection because of their dependence on professional interpretation. The proposed system uses artificial intelligence technologies to improve diagnostic precision thus enabling fast and efficient detection processes.

The World Health Organization (WHO) states TB infections affect approximately 10 million patients yearly because many cases remain unidentified or misidentified because there are not enough radiologists. An AI-powered diagnostic system functions as the primary task in this research to provide automatic tuberculosis detection capability in chest X-rays for swift and dependable medical outcomes. The approach will provide essential benefits to regions that lack enough medical experts.

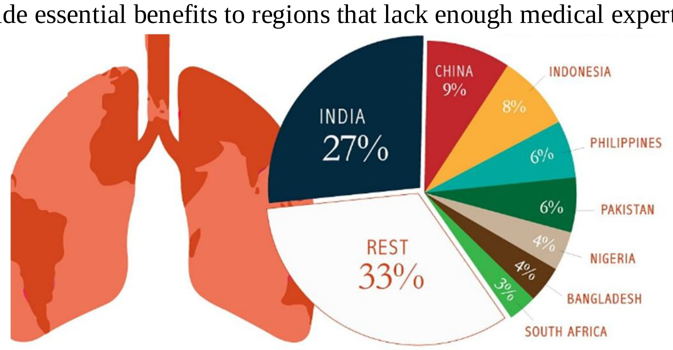

Figure 1: Percentage of PTB Patients in the world

High-burden countries that include India alongside China and Indonesia together with the Philippines and Nigeria hold responsibility for most TB cases. TB incidence rates stand particularly high across Uttar Pradesh and Bihar and Maharashtra and Madhya Pradesh states within India because these areas need special intervention strategies. Developing nations together with states which both have numerous inhabitants and scarce healthcare systems require affordable and scalable diagnostic tools to address their high prevalence of TB.

The Chest X-ray Pulmonary Tuberculosis Detection System develops a deep learning platform that uses X-ray images for automatic tuberculosis pathology identification. Deep learning analytics enable the system to provide precise medical image diagnoses that both minimize radiologists' requirement and deliver both faster and more reliable outcomes.

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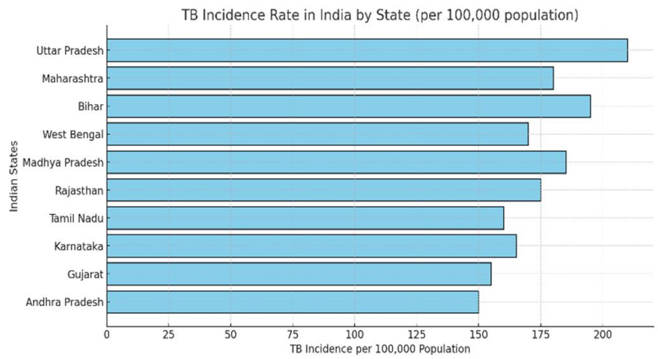

Figure 2: TB Incidence Rate

Different regions show varying levels of TB prevalence while high-burden nations including India along with China and Indonesia with the Philippines and Nigeria play the biggest role worldwide in TB case numbers. The states of Uttar Pradesh and Maharashtra and Bihar demonstrate the highest incidence rates of TB in India which shows the importance of providing diagnosis solutions that will reach those areas. The high frequency of TB occurrences requires innovative portable testing systems that can help combat the disease more effectively.

Deep learning technologies integrated into mobile testing software serve as this project's main objective to offer prompt and precise medical diagnosis for people who need it particularly in remote regions. The system features two functions - X-ray detection of TB alongside symptom-based assessment and prevention strategies and doctor recommendation tools for better disease management and control strategies.

II. RELATED WORK

Different investigations examine how deep learning models detect tuberculosis from chest X-ray images. Multiple researchers have incorporated different convolutional neural networks (CNN) structures along with combination techniques and image preprocessing steps for improving the diagnostic performance and interpretation capabilities of tuberculosis detection algorithms.

This research study in [1] deployed a deep learning model for training on 1,196 X-ray images from Kaggle which yielded an accuracy of 94%. The research confirmed that CNNs created efficient automated TB identification protocols which performed with exceptional accuracy. The authors of [2] performed an extensive evaluation of deep learning algorithms targeting TB diagnosis which included a review of Shenzhen X-ray images together with Montgomery images and TBX11K X-ray data while identifying barriers in reaching clinical validity standards. The authors of [4] developed a diagnostic system using VGG16 architecture with coordinate attention mechanisms to address the misdiagnosis problems that occur in non-automated methods.Transfer learning techniques serve as an alternative approach for detecting tuberculosis in medical samples. Testing nine different CNN models with ResNet and DenseNet among them took place in [5]. Research in [6] integrated visualization methods including Grad-CAM into deep learning techniques for highlighting infected lung regions to improve medical professional understanding of results. The authors in [7] developed segmentation along with heatmap technology to enhance the detection of lesions in lungs affected by TB.

Somewhat novel classification methods utilized CNNs together with machine learning algorithms in their exploration of TB detection according to [8]. To enhance model performance the study demonstrated that proper preprocessing measures such as contrast enhancement in addition to lung region cropping need to be implemented.

The research reported in [9] found that deep learning models especially CNNs provided improved accuracy and feature extraction performances over traditional support vector machines (SVM) and decision trees. Researchers in [10] studied various preprocessing steps which achieved better classification precision through joint application of contrast enhancement with region-of-interest segmentation.

III. OBJECTIVE

This study aims to establish a mobile application for pulmonary tuberculosis detection by implementing convolutional neural networks (CNNs) as deep learning techniques. Through X-ray image evaluation the system helps detect TB with accuracy while reducing reliance on human radiologists to discover conditions early in locations with limited healthcare resources. Users will have access to a symptom-based assessment module in the application that lets them report their symptoms for evaluation purposes. X-ray analysis together with symptom-based risk evaluation facilitates more precise diagnosis while reducing incorrect negative results.

The research project focuses on developing a mobile application which detects pulmonary tuberculosis by using convolutional neural networks (CNNs) as deep learning techniques. The system uses X-ray image evaluation to detect TB accurately and lowers the necessity of human radiologist involvement for early condition detection particularly in areas with restricted healthcare resources. Through the application users will be able to utilize a symptom-based assessment module which enables them to report their symptoms until assessments are complete.

IV. PURPOSE

The developed chest X-ray pulmonary tuberculosis detection system uses deep learning and machine learning to establish an automated and precise system that helps identify tuberculosis early when employed through mobile or web-based platforms. This computer system employs advanced algorithms for precise chest X-ray image analysis thus it shortens diagnostic durations while needing fewer radiologists for interpretation. The system provides access through mobile devices together with web platforms which ensures it can serve limited-resource environments. This system links image assessment techniques with symptom testing methods to perform complete detection while generating easy-to-understand reports containing visual information for users. The system benefits global tuberculosis detection and patient management through deep learning models and efficient data processing alongside an intuitive interface which helps lower transmission rates.

V. PROPOSED SYSTEM

The proposed system has four distinct elements. The Image-Based Diagnosis system applies CNN models to classify TB using preprocessing operations including image normalization together with contrast enhancement to achieve higher accuracy levels. An X-ray image receives its TB-positive or negative classification through the combination of feature extraction together with classification processes. Through Symptom-Based Diagnosis users can complete a structured symptom survey while machine learning analyzes symptom patterns to establish patient risk levels. Hybrid models that merge image analysis with symptom testing produce superior detection accuracy. The implementation phase of the mobile app uses Android Studio together with Django for its backend and a secure MySQL database to store diagnostic results and user history. The mobile application provides users with three main features which are medication tracking alongside doctor appointment reminders with scalable cloud storage. Model Optimization and Deployment uses TensorFlow Lite for mobile device efficiency while compression techniques such as quantization reduce the computational and memory requirements of the system. The system gains better reliability by adopting real-time feedback which adapts the model based on user inputs.

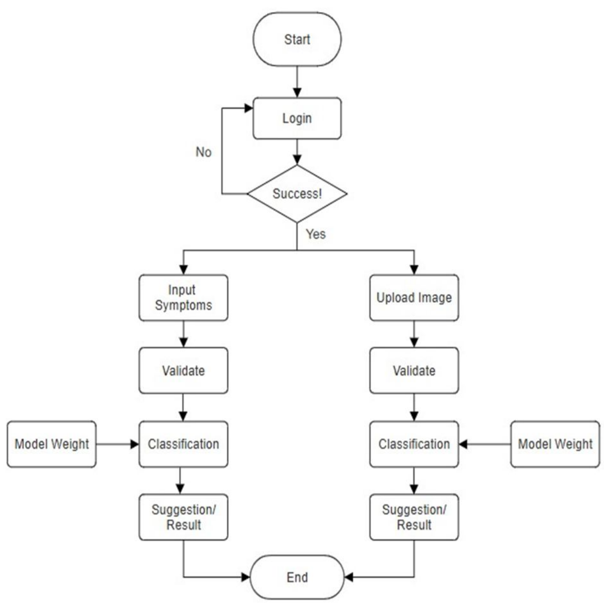

Figure 3: Flow Chart

A Pulmonary Tuberculosis (PTB) detection system with symptom-based input and image classification operates according to Figure 3. The structured procedure of the system initiates with user verification and eventually moves towards disease identification by various evaluation techniques.

A. Login and Authentication

A process starts at Start before moving to the Login requirement which demands user authentication. After a user completes the login process the system verifies the authentication success. The system stops the user from continuing after an unsuccessful login attempt. "The system advances to the following phase after a successful login which allows users to either provide symptoms by hand or upload imagery for assessment".

B. Symptoms-Based Classification Path

The system requires users to input symptoms regarding TB under this initial method. After validating the entered information, the system checks for accuracy and completeness of the input. The validated symptoms move through a classification model that utilizes predefined model weights to make TB likelihood predictions. Following the processing step the system presents its proposed outcome to the end-user. The system ends processing at this stage when the classification decision becomes conclusive.

C. Image-Based Classification Path

A user has the option to upload chest X-ray images for TB detection purposes. A validation process verifies whether the uploaded image represents proper medical images in much the same way as symptoms-based detection. A validated image moves to the classification model for processing through comparison with model weights to detect TB patterns. The system generates the final classification outcome which produces a result to be presented.

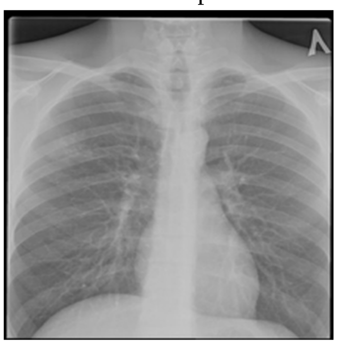

Figure 4: PTB Positive

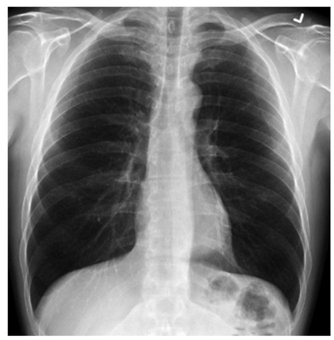

Figure 5: PTB Negative

D. Model Weight Utilization

During the classification step both symptom-based and image-based pathways apply the established model weights. The system utilizes weights developed during previous machine learning training of TB cases from a dataset which enables predictive accuracy. The model operates persistently to process fresh inputs thus enhancing medical diagnosis capabilities.

E. Final Output and Completion

When classification finishes the system will display both detection results about TB together with possible doctor referral or extra test advice to the user. The results of the diagnostic process appear to indicate the conclusion of this workflow sequence.

VI. METHODOLOGY

The Chest X-ray Pulmonary Tuberculosis Detection System development process combines deep learning and mobile application development with user-centred design. The system core includes elements which offer tuberculosis detection through X-ray imaging using powerful algorithms that maintain reliability and scalable capabilities. The following details the complete methodology:

1) Problem Analysis and Requirement: System Gathering establishes both the hurdles of detecting TB and it observes how users expect healthcare services to work. The system specifies essential features to handle image uploads combined with symptom data entry while presenting diagnostic outcomes to users for an effective and easy-to-use approach.
2) Dataset Collection and Preprocessing: The first step requires collecting X-ray images with identified markers for training purposes. To ensure consistency the data receives preprocessing steps which include resizing and normalization and quality enhancement. An effective model learning process is supported through the split of the dataset into training, validation and testing subsets.

$$X_{\text{train}}, X_{\text{test}}, y_{\text{train}}, y_{\text{test}} = \text{train\_test\_split}(X, y, \text{test\_size} = 0.10)$$

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3) Model Development: The main focus of this project involves creating a specialized Convolutional Neural Network (CNN) for identifying TB. The trained model uses the processed data to execute identification of both TB-positive and negative specimens with high accuracy rates. The system's reliability and diagnostic precision totally depend on this fundamental stage.

$$O(x,y) = \sum_i \sum_j I(x-i, y-j) \cdot K(i,j)$$

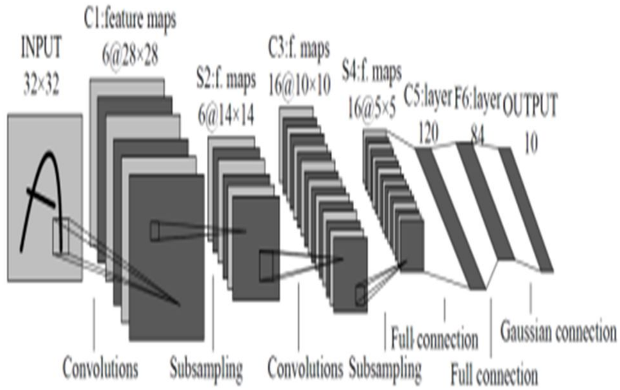

Figure 6: CNN Architecture

4) Symptom-Based Analysis: The system offers users a method to provide symptom information including cough alongside fever and weight loss by using structured questionnaires. The analysis of obtained symptom information merges with image data to produce improved diagnostic certainty which results in enhanced diagnosis precision.

$$P(TB) = \frac{1}{1 + e^{-(\beta_0 + \sum \beta_i x_i)}}$$

5) App Development: The development process includes making applications for mobile or web platforms with Android Studio (Java), and the combination of HTML, CSS and JavaScript. The application utilizes Django principles for backend management that supports picture upload functions and model detection protocol
6) Prevention Strategies and Recommendations: The system should focus on educating users about preventing TB through ventilation improvement and avoiding crowded spaces. Through the user feed system users can receive personalized health improvement suggestions which use diagnostic results and user inputs to guide informed health decisions.
7) Testing and Validation: The model undergoes rigorous testing to guarantee accuracy and usability and performance of the system. The model endures multiple reliability tests before deployment and application evaluation includes usability testing to achieve smooth functionality.
8) Deployment and Maintenance: The initial deployment of the application must begin with releasing it to relevant platforms including Android. The system operates under continuous performance evaluation with user feedback processing leading to the enhancement of features over time.

VII. IMPLEMENTATION

The three-tier design of the system requires the integration of EfficientNetV2 for classification and SegResNet for segmentation to diagnose tuberculosis within chest X-rays. Image features move up through hierarchical stages after convolution operations together with pooling and dense connections run their processing sequence on the images. Before classification the system uses CLAHE and segmentation to optimize image quality through preprocessors. The system accepts supplemental datasets together with techniques including pseudo-labelling and maintains its fundamental structural components unchanged. Final output receives user action yet the system hides its feature representation details from end users.

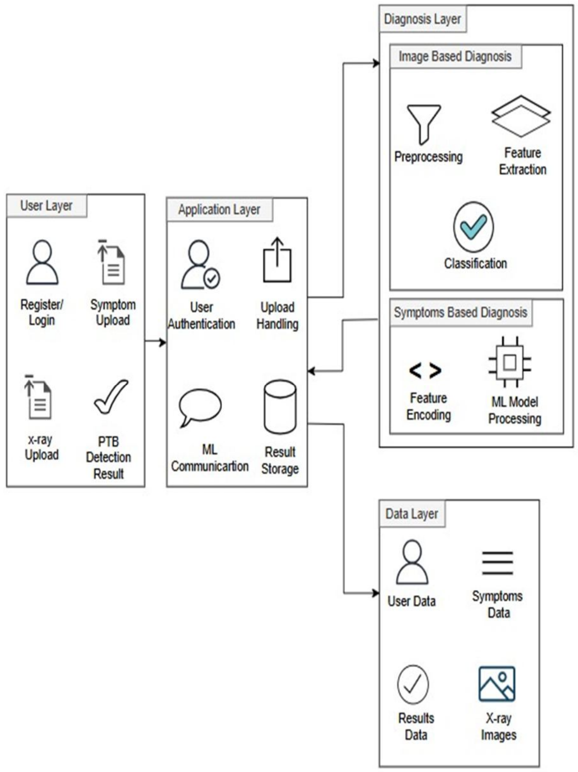

Figure 4: System Architecture

Django framework enables the presentation layer to display diagnostic results but the business logic is implemented through PyTorch or TensorFlow model operations. Preprocessed images and results from the system get stored in MySQL or cloud storage platforms.

1) User Layer: The construction of the TB detection system follows an organized strategy, which begins with the creation of a secure authentication system that allows users to register and log in. The program must provide symptom upload capabilities, which allows users to enter their symptoms via a standardized questionnaire. In addition, an image upload capability must be built so that customers can submit chest X-rays for study. The system should then display the PTB detection results in a clear and user-friendly manner.
2) The Application Layer: Concentrates on backend functionalities. User authentication is handled using Django's authentication system or Firebase for safe access. Upload handling systems must be in place in order to efficiently manage X-ray and symptom data uploads. Machine learning communication is used to process the uploaded data, ensuring a smooth connection between the user interface and the ML models. Furthermore, results must be securely maintained in a MySQL database so that users can view their diagnostic history whenever necessary.
3) The Diagnosis Layer: The implementation consists of two primary components: image-based and symptom-based diagnostics. A preprocessing pipeline for Image-Based Diagnosis is created to improve X-ray pictures by normalizing and adjusting the contrast. Convolutional Neural Networks (CNNs) are used to extract features from images and find important patterns. A trained classification model is then used to identify whether an X-ray image shows tuberculosis positivity or negative. Symptom-Based Diagnosis employs a feature encoding approach to translate user symptoms into a structured format appropriate for machine learning analysis. A machine learning algorithm is built to identify symptom patterns and assess the risk of tuberculosis, supplementing the image-based diagnosis for a more thorough review.
4) The Data Layer: Provides secure and efficient data storage. A MySQL database is intended to hold user information, symptom data, diagnostic results, and submitted X-ray images. The database must be appropriately indexed and optimized to enable for speedy retrieval and seamless operation. To secure sensitive user data, security procedures like encryption and authentication must be used.

5) Backend Integration: Django-based API endpoints are created to manage image and symptom uploads, interface with ML models, and get results. Security procedures, such as encryption and authentication tokens, must be established to safeguard user privacy and ensure data transfer safety. These backend services provide seamless interaction between the mobile application and ML models.

VIII. RESULT

The model was trained across five epochs, and its performance was measured using training loss, validation loss, training accuracy, and validation accuracy. The training loss decreased consistently, from 0.4583 in the first epoch to 0.0842 in the last epoch, demonstrating effective learning. Similarly, the validation loss first decreased from 0.3214 to 0.1216, but then increased slightly in the fourth epoch before settling at 0.1229 in the final epoch.

The training accuracy gradually improved, beginning at 81.05% and reaching 96.50% by the last period. The validation accuracy followed a similar pattern, peaking at 97.02% at epoch three and settling at 96.90%, confirming the model's great generalizability. Following training, the model was tested and achieved an excellent accuracy of 95.72%, demonstrating its durability and efficacy. These findings indicate that the model successfully learns the patterns in the dataset while minimizing overfitting.

A confusion matrix was created based on the test results to evaluate the model's performance further. The model's accuracy was 94.64%, with 52 true positives, 1 true negative, 3 false positives, and 0 false negatives. This shows that the model has a high ability to accurately classify positive examples while marginally misclassifying a few negative samples. The absence of false negatives indicates high sensitivity, implying that the model effectively detects positive cases. These findings demonstrate the model's reliability for real-world applications and suggest areas for further development.

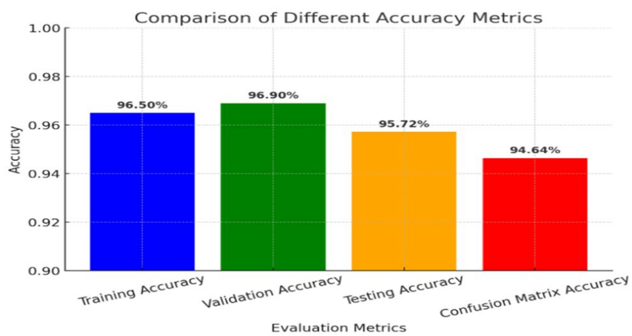

Figure 8: Comparison of Training, Validation, Testing, and Confusion Matrix Accuracies.

IX. CONCLUSION

The System has successfully built a mobile application for early detection of pulmonary tuberculosis utilizing chest X-ray pictures. The technology produces reliable and efficient diagnostic results, decreasing the need for radiologists to analyze data manually. The results show that the suggested methodology improves early detection, treatment outcomes, and TB transmission. The application's user-friendly interface and extra capabilities, such as symptom-based analysis and prevention measures, make it a comprehensive tool for tuberculosis management. Future work will focus on increasing the dataset, enhancing the model's accuracy, and including real-time medical consultation elements to further increase the system's capabilities.

X. ACKNOWLEDGMENT

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