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Empowering Tuberculosis Diagnosis with Deep Learning: Unveiling the Strengths of Xception and DenseNet

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***Abstract*-Mycobacterium tuberculosis is a bacterium which causes TB(Tuberculosis). It can easily pass/transfer from one person to another. It is one of the major health problems particularly in developing countries. Tuberculosis can be detected in a person depending on some symptoms, and from analyzing the CXR (Chest X-Ray). Under this scenario, fast detection of TB is important and is must for quick treatment, recovery and control of the disease. One of the reliable tests to detect TB is Isolating the bacteria which causes TB this is an effective method to detect TB but takes more time to get report and a bit expensive. As early detection of TB is very important for control of disease So, in current study we'll use deep learning to address this issue and find to better way to diagnose Tuberculosis with low cost and high specificity. Comparing different models in deep learning we'll find best model which works effectively for Tuberculosis. After analyzing CBAMDensenet, WideResnet, Densenet, Resnet, Xception, Inception etc. Xcepion surpasses all the model in accuracy making it very good and efficient for TB diagnosis using CXR**

Index Terms-Chest X-ray, convolutional neural network, deep learning, disease diagnosis, tuberculosis

I. INTRODUCTION

Infectious tuberculosis (TB), caused by the Mycobacterium tuberculosis, is a significant health concern worldwide, especially in developing countries. Traditionally, diagnosing tuberculosis relies on recognizing symptoms, analyzing chest X-rays (CXR), and reviewing medical records. An accurate and efficient diagnosis method is crucial for effective treatment and disease control. Isolating the bacteria remains the most dependable method for confirming TB cases. However, this technique, while highly specific, suffers from relatively low sensitivity. Consequently, obtaining test results can take more time. Other diagnostic methods, like immunological and molecular biology tests, offer some advantages and disadvantages Early diagnosis is vital for the timely treatment and control of TB's spread. In response to this challenge, different ML and DL models are being increasingly utilized to tackle this issue.

II. OJECTIVE

Despite its potential, deploying deep learning for tuberculosis detection faces significant hurdles. A primary challenge is the necessity for labeled medical image datasets, essential for effective model training and validation. Acquiring these datasets is often difficult due to privacy concerns. Our goal is to identify the optimal model for this issue and develop an application utilizing that model which will be used to address this issue.

III. PROBLEM STATEMENT

Millions around the globe suffer from tuberculosis, a highly contagious and potentially deadly infectious disease. Early detection is vital for initiating effective treatment and preventing its spread. This paper proposes Xception and some other innovative DL model designed for TB detection through chest X-ray image processing after analyzing and comparing different models finding best model of all.

IV. EXISTING WORK

Researchers have explored the application of Artificial Neural Networks (ANNs) for tuberculosis detection, proposing various Convolutional Neural Network (CNN) architectures paired with Support Vector Machine (SVM) classifiers. These models have demonstrated promising results, achieving accuracy rates of approximately 80-90%.

V. DISADVANTAGES OF EXISTING WORK:

To the best of my understanding, Existing work is not defined to capture the important sections of the image which are crucial for prediction task. Additionally, the computation cost is high. Existing approaches also face issues such as the "Vanishing Gradient" problem.

VI. PROPOSED WORK

In the proposed work, we use:

CBAM WDnet: To effectively capture spatial and contextual information.

Xception: To reduce computation through depth-wise separable convolutions.

DenseNet: To enhance feature extraction by providing each layer with feature maps from all preceding layers.

Wide ResNet: To address gradient descent issues and reduce computation by employing residual blocks and additional convolution filters, without excessively increasing the network depth.

The system aims to enable early detection of tuberculosis and improve healthcare outcomes

VII. ADVANTAGES OF PROPOSED SYSTEM

In proposed work, as we are comparing different the models which address existing work issues and try to solve those issues

CBAM WDNet: This method, while slightly increasing computational and memory demands, can significantly enhance classification performance. Its design improves attention to spatial and contextual information in X-ray images.

Xception: Xception is effective in reducing computational costs while preserving data quality through its depth-wise separable convolution method.

DenseNet This architecture addresses the vanishing gradient problem effectively by employing numerous layers that maximize feature extraction.

Wide ResNet: Wide ResNet employs residual blocks and additional filters within a less deep network, reducing both computational costs and gradient descent issues.

VIII. LITERATURE SURVEY

The ongoing global challenge of tuberculosis (TB), a disease caused by the bacterium Mycobacterium tuberculosis, has driven significant research into improving diagnostic methods and treatment strategies. Traditional diagnostic approaches have primarily relied on culturing the bacteria from clinical samples, which, despite its high specificity, often results in delayed diagnoses due to its low sensitivity and lengthy processing time. As a result, there has been a growing emphasis on developing faster, more accurate diagnostic techniques. In recent years, advancements in molecular and imaging technologies have paved the way for significant progress in TB detection.

Molecular and immunological diagnostic methods offer promising alternatives to traditional culturing. Cho [2] provided a comprehensive overview of current issues surrounding molecular and immunological TB diagnostics. These methods include nucleic acid amplification tests such as polymerase chain reaction (PCR), which offer higher sensitivity and quicker results compared to traditional methods. However, they can be expensive and are not universally available, limiting their accessibility in resource-limited settings. Cho's review highlighted the balance between these methods' benefits and their limitations, emphasizing the need for continued innovation to address these challenges effectively.

Imaging techniques, particularly chest X-rays (CXR), play a critical role in TB diagnosis. The use of deep learning to enhance CXR-based screening for TB has gained traction in recent research. Pasa et al. [15] explored efficient deep network architectures for fast chest X-ray TB screening, presenting a method that leverages deep learning to expedite and enhance the accuracy of TB detection. Their approach demonstrated significant improvements in both speed and accuracy, addressing some of the limitations of traditional imaging techniques. Similarly, Rahman et al. [19] focused on reliable TB detection using chest X-rays combined with deep learning, segmentation, and visualization techniques. Their work underscored the potential of integrating advanced machine learning techniques with traditional imaging to improve diagnostic performance.

In addition to direct imaging improvements, there has been considerable research into combining imaging with other diagnostic strategies. Melendez et al. [16] proposed an automated TB screening strategy that integrates X-ray-based computer-aided detection with clinical information. This combination of approaches allows for more comprehensive and accurate screening by leveraging the strengths of both imaging and clinical data. Their work highlights the effectiveness of multi-modal diagnostic strategies in improving TB detection and management.

Feature selection is another crucial area in the development of automatic TB screening systems. Vajda et al. [17] investigated feature selection techniques for automatic TB screening in frontal chest radiographs. By focusing on identifying the most relevant features for TB detection, their research aimed to enhance the efficiency and accuracy of automated screening systems. This work is particularly important as it addresses the challenge of optimizing machine learning models for TB detection by selecting the most informative features from imaging data.The use of pre-trained convolutional neural networks (CNNs) as feature extractors has also emerged as a valuable approach in TB detection. Lopes and Valiati [18] explored this method, demonstrating that pre-trained CNNs can be effectively utilized to extract relevant features for TB detection from chest X-rays. Their research highlights the advantages of leveraging pre-existing deep learning models, which have been trained on large datasets, to improve the accuracy of TB detection in new contexts.

The integration of advanced machine learning techniques with traditional diagnostic methods has shown promising results in improving TB detection. The application of CNNs, in particular, has been transformative in enhancing the performance of diagnostic systems. By utilizing deep learning techniques, researchers have been able to develop more accurate and efficient diagnostic tools, addressing some of the limitations of traditional methods.

Furthermore, the emphasis on developing rapid and reliable diagnostic methods aligns with the critical need for timely TB detection and treatment. The continued advancement of molecular, imaging, and machine learning technologies holds the potential to significantly improve TB diagnosis and management, ultimately contributing to better public health outcomes.

Overall, the literature demonstrates a clear trend toward integrating advanced technologies with traditional diagnostic methods to improve TB detection. The combination of deep learning, feature selection, and multi-modal approaches represents a significant advancement in the field, offering new possibilities for faster and more accurate TB diagnosis. Continued research and development in these areas are essential for addressing the ongoing challenges of tuberculosis and enhancing global health efforts to combat this pervasive disease.

IX. SYSTEM DESIGN

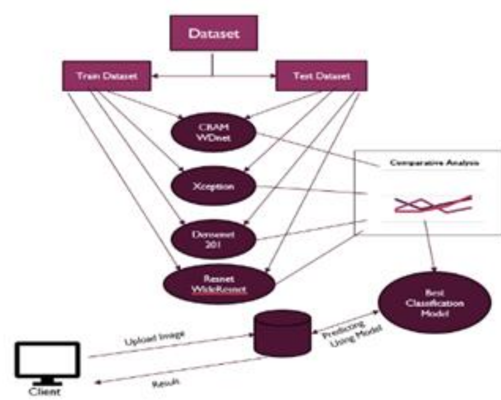

Fig 1 Proposed System Design

X.IMPLEMENTATION

a) Data Collection: We’ll collect data of Tuberculosis and Normal patients CXR (Chest X-Ray) images available in public domain [23]Additionally, the TB chest X-ray dataset, compiled by Qatar University, University of Dhaka, and their collaborators, includes 700 TB-diagnosed and 3500 normal CXR images

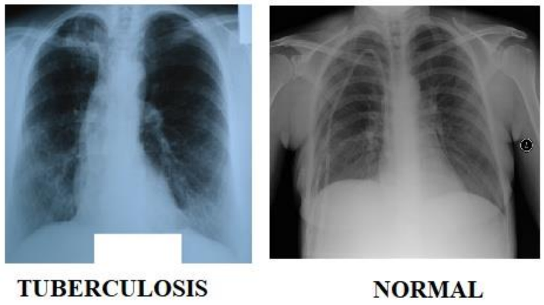

Fig 2 Sample Dataset Image

b)Data pre-processing**:** All of the images in the Tuberculosis dataset are shrunk to 128 by 128 pixels in this stage. All photos are guaranteed to be appropriate for a deep learning model, namely a Convolutional Neural Network (CNN), thanks to this scaling. We set up the data for consistent input to the trained model by standardizing all photos to 128 by 128 pixels. This procedure facilitates the model's effective learning from the training dataset and helps it generalize, which facilitates the identification and classification of features in the test dataset.

C)Data Splitting: Split the data into 2 parts for training and validation in here 70% of data is for training and 30% is for validation. Generator, we begin with re-scaling the images to normalize their pixel values, ensuring consistency across the dataset. Shear transformation is applied to introduce variations in the images by applying a shear angle, which helps the model generalize better to different perspectives. Zooming the image further enhances the model's robustness by allowing it to learn from various levels of magnification. Horizontal flipping is used to mirror the images, increasing the dataset's diversity and helping the model become invariant to left-right orientation changes.

d)Different DL models building and analyzing their accuracy and loss:

ResNet :Resnet is a deep learning model that uses residual connections to learn complex patterns in images ,This helps toPreserve input information**,** Address vanishing gradients issueEnable us to work with deeper networks Can Learn complex patterns with good accuracy

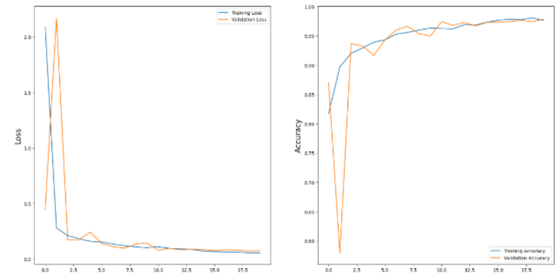

Fig 3 Comparison graph of Training & Validation Loss and Accuracy

DenseNet: DenseNet (Densely Connected Convolutional Networks) is a DL Model that connects each layer to all the previous layers in a feed-forward fashion. This design:Encourages feature reuse and propagation of features to forward layers, leading to more efficient learning, mitigates vanishing gradients, enabling deeper networks, Reduces the number of parameters, making it more computationally efficient, Enhances overall model accuracy and performance

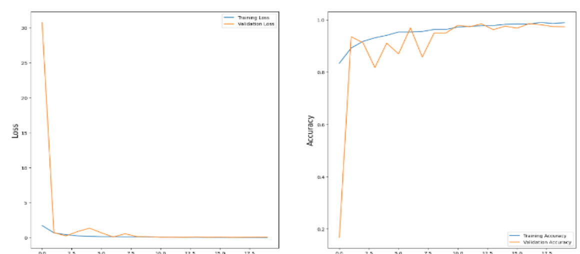

Fig 4 Comparison graph of Training & Validation Loss and Accuracy

Xception: The Xception model is a groundbreaking neural network architecture that has revolutionized image classification tasks with its exceptional performance. Inspired by the Inception modules, Xception's innovative design employs depth wise separable convolutions, optimizing processing efficiency and improving accuracy.

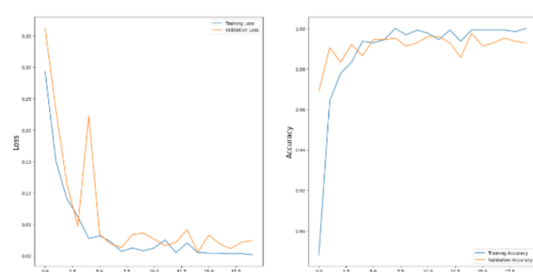

Fig 5 Comparison graph of Training & Validation Loss and Accuracy

WideResNet:Wide Residual Networks increase the number of convolution filters in the first few layers . Instead of going deeper with more layers, WideResNet use more filters per layer increasing width of layers, which helps to decrease computational costs while still enhancing the ability to learn complex features. By balancing the network's depth and width, this method enhances performance without appreciably adding to the computational load.

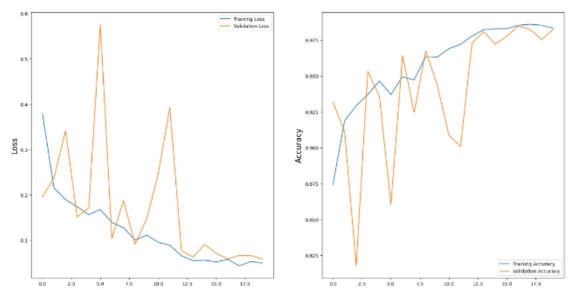

Fig 7 Comparison graph of Training & Validation Loss and Accuracy

CBAMWDnet:A neural network that combines spatial and channel attention mechanisms to focus on important features in an image, hence improving performance of the model focusing on crucial parts of image.

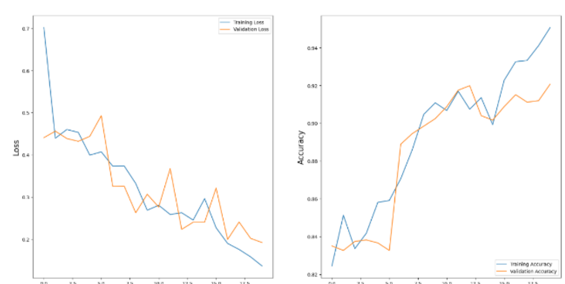

Fig 6 Comparison graph of Training & Validation Loss and Accuracy

AlexNet: AlexNet's architecture allows it to:Learn hierarchical representations of images, capture complex patterns and features, Achieve great performance on image classification tasks

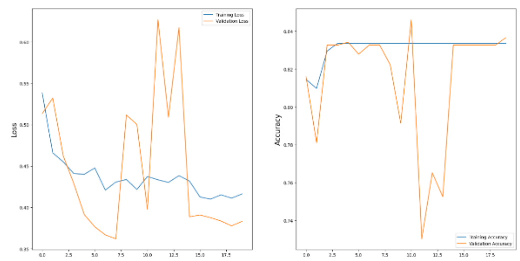

Fig 8 Comparison graph of Training & Validation Loss and Accuracy

Inception – Inception-v3 is a convolutional [18] neural network that is 48 layers deep. You can load a pretrained version of the network trained on more than a million images from the ImageNet database [1]. The pretrained network can classify images into 1000 object categories .

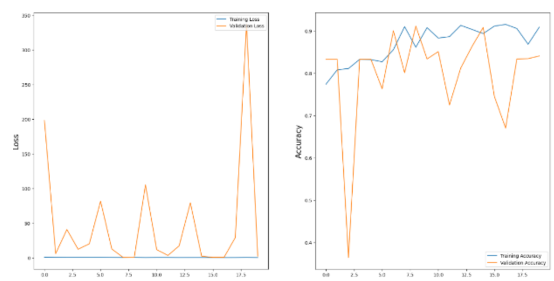

Fig 9 Comparison graph of Training & Validation Loss and Accuracy

Early stopping Mechanism: During deep learning model training, iterative epochs are used to refine performance. To optimize results and prevent overfitting, early stopping is employed. This involves monitoring training and validation loss after each epoch. If validation loss tends to improve, training is terminated, protecting our model against overfitting and improve model ability to capture more generalized features.

XI EXPERIMANTAL RESULTS

Comparing all trained models:We'll analyze all trained models using metrics such as accuracy, F1 score, precision, and recall. By evaluating these metrics, we can determine the best-performing model among them. This comprehensive analysis ensures that the chosen model not only performs well overall but also balances the trade-offs between precision and recall, providing robust and reliable results.

	ML Model	Accuracy	Precision	Recall	F1-Score
0	ResNet50	0.979	0.979	0.979	0.979
1	AlexNet	0.837	0.837	0.837	0.837
2	SqueezeNet	0.833	0.833	0.833	0.833
3	DenseNet	0.974	0.974	0.974	0.974
4	InceptionV3	0.841	0.841	0.841	0.841
5	Wide ResNet	0.983	0.983	0.983	0.983
6	CBAMDense	0.921	0.921	0.921	0.921
7	Xception	0.993	0.993	0.993	0.993

Fig 10 Comparison Table

Accuracy: The accuracy of a diagnostic test refers to its capacity to accurately distinguish between individuals with the disease (patients) and those without it (healthy cases). To determine test accuracy, we calculate the proportion of correctly identified true positives (TP) and true negatives (TN) out of all cases evaluated. This can be expressed mathematically as: Accuracy = (TP + TN) / (TP + TN + FP + FN), where FP and FN represent false positives and false negatives, respectively.

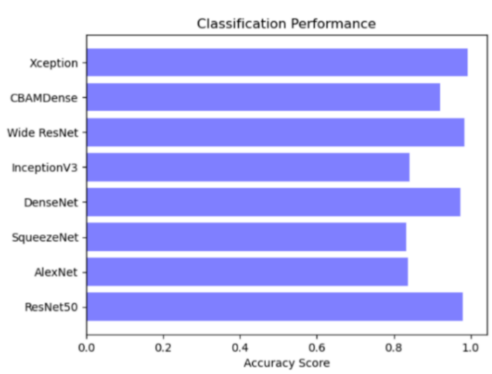

Fig 11 Accuracy Comparison

Precision: Precision measures the accuracy of positive predictions made by a test or model. It calculates the proportion of true positives (correctly identified instances) among all positive predictions, including both true positives and false positives. The precision formula is: Precision = TP / (TP + FP), where TP represents true positives and FP represents false positives. This metric helps evaluate the reliability of positive results, ensuring that actual positives are accurately identified.

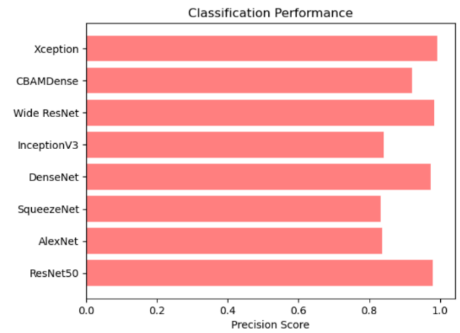

Fig 12 Accuracy Comparison

Recall: Recall is a key performance metric in machine learning that evaluates a model's ability to detect all instances of a specific class. It calculates the proportion of true positives (correctly predicted instances) among all actual positive cases, providing a measure of the model's comprehensiveness in identifying relevant instances. Mathematically, recall is expressed as: Recall = TP / (TP + FN), where TP represents true positives and FN represents false negatives. A high recall indicates that the model is effective in capturing most instances of the class, minimizing false negatives.

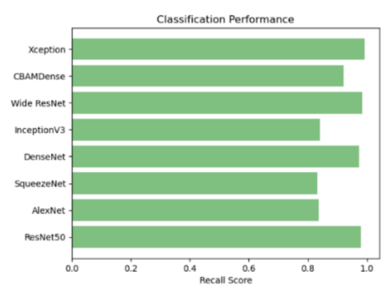

Fig 13 F1 Score Comparison

F1-Score**:**The F1 score calculates the model's accuracy as the weighted average of precision and recall, offering a more nuanced understanding of its performance. By considering both false positives and false negatives, the F1 score provides a more complete picture of a model's accuracy, making it a valuable metric for evaluating model performance.

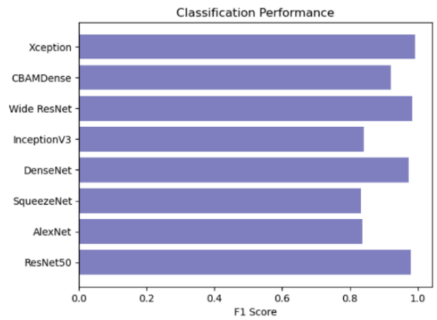

Fig 14 F1 Score Comparison

Frontend building integration and results:

Once we identify the best-performing model, we will save it with a `.h5` extension. This saved model will be used for prediction and providing results for user-uploaded images. We'll build an application using Flask that allows users to upload images. The application will use the saved model to predict and display the results to the user.

The main functionalities of the frontend are as follows: User Registration: Allow users to register and sign in.

Image Upload: Enable users to upload an image in the specified formats.

Display Results: Show the prediction results to the user after processing the uploaded image.

This user-friendly interface ensures that users can easily interact with the application, from registration to viewing the results of their image analysis.

User Signup Page:

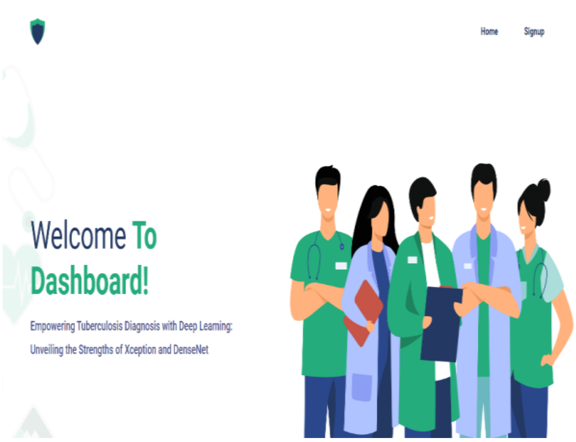

Fig 15 Home Page

User Registration page:

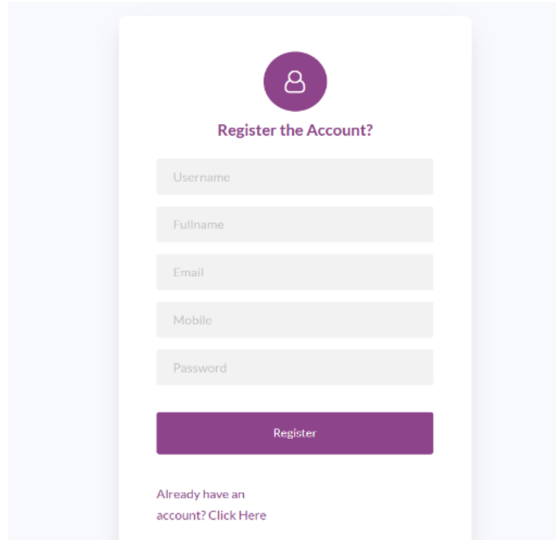

Fig 16 User Registration

User login page:

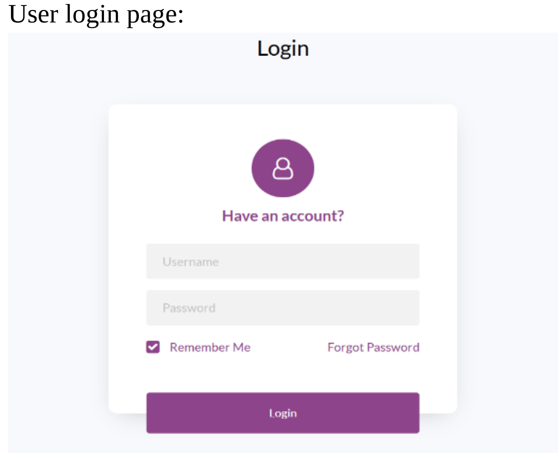

Fig 17Login Page

Upload image to Predict:

Fig 18Upload Page

Prediction page:

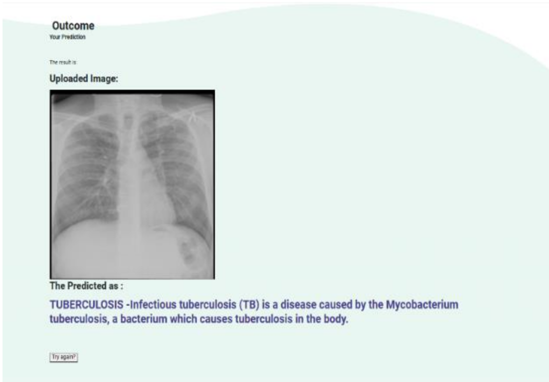

Fig 19Prediction Page

XII. CONCLUSION

The study found that CBAM WDNet, as well as other models like DenseNet, Xception, and WideResNet, outperformed all other models, achieving high and satisfactory accuracy of 98% and above. Consequently, we will use the model with the highest accuracy to build a frontend using Flask. This application will allow users to upload chest X-ray images and receive diagnostic results. By leveraging deep learning, we successfully addressed and resolved a significant issue in tuberculosis detection.

XIII. FUTURE SCOPE

Diverse Disease Adaptation: Customize the model to diagnose various health conditions beyond tuberculosis. This approach involves training the model on datasets related to different diseases, enabling it to detect a wide range of medical issues. By doing so, the system can become a versatile diagnostic tool for various health conditions. Additionally, we will build different models tailored for specific diseases and integrate them into our application, enhancing its capability to provide accurate diagnoses for multiple health conditions.

Medical Field Integration:Expand the application to be integrated into clinical settings. This includes collaborating with healthcare professionals to ensure the system meets clinical standards and can be seamlessly incorporated into existing workflows. Extensive testing and refinement will be conducted to ensure the application is reliable and effective for broader healthcare use. By embedding the system into clinical environments, we can support healthcare professionals in providing timely and accurate diagnoses, ultimately improving patient outcomes.

In summary, by tailoring the model for various health conditions, building specific models for different diseases, and integrating these capabilities into our application, we aim to create a comprehensive diagnostic tool that can be effectively utilized in diverse medical scenarios.

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