Deep Learning-Based Approach for Classification of Tuberculosis for Improved Patient Diagnosis

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ABSTRACT

Tuberculosis (TB) remains a significant global health threat, responsible for millions of deaths annually. Traditional diagnostic methods, such as sputum smear microscopy and chest X-rays, are often time-consuming, subjective, and limited in detecting early-stage TB or differentiating it from other lung diseases. With the rise of deep learning technologies, automated classification of TB using medical imaging presents a promising solution for improving diagnosis accuracy and speed. Historically, medical professionals have relied on manual interpretation of chest X-rays, which is prone to errors due to variability in expertise and image quality. This challenge, coupled with limited resources in many high-burden regions, underscores the need for a more reliable, automated system. In this research, we propose a deep learning-based approach for classifying TB using chest X-ray images. Leveraging convolutional neural networks (CNNs), this system can automatically detect TB-related features in medical images with high accuracy. The proposed model offers significant improvements over traditional methods by providing faster, consistent, and more accurate results, especially in resource-limited settings. This data-driven approach holds great potential in aiding healthcare professionals in TB diagnosis and reducing the disease's global burden.

Keywords: Tuberculosis detection, Chest x-rays, Deep learning, Convolutional neural networks (CNNs), Medical image classification.

1. INTRODUCTION

Tuberculosis (TB) is one of the oldest known infectious diseases, caused by *Mycobacterium tuberculosis*, and remains a major global health concern. According to the World Health Organization (WHO), India accounts for nearly 27% of global TB cases, making it the highest TB-burdened country. Despite advancements in medical technology, TB diagnosis remains challenging, particularly in rural and resource-limited settings. Traditional diagnostic methods, such as sputum smear microscopy, are time-consuming and have limited sensitivity, especially in detecting latent or drug-resistant TB. Chest X-rays (CXRs) are commonly used for TB screening, but manual interpretation is prone to errors due to variability in radiologists' expertise and image quality. The emergence of deep learning and artificial intelligence (AI)-driven approaches has opened new possibilities for automating TB detection with greater accuracy and speed. Convolutional Neural Networks (CNNs), a subset of deep learning, can analyze complex patterns in medical images, providing reliable and objective TB classification. By leveraging large-scale TB image datasets, these AI-driven systems can support early detection, reduce misdiagnosis rates, and assist healthcare professionals in decision-making. This research aims to develop a deep learning-based TB classification model that enhances diagnostic efficiency, particularly in high-burden areas like India. Before the adoption of machine learning in medical diagnostics, TB detection relied heavily on traditional methods like sputum smear microscopy, chest radiography, and the tuberculin skin test. These methods have several limitations, including low sensitivity in early-stage

TB, difficulty in distinguishing TB from other lung infections, and long turnaround times for results. Furthermore, sputum-based tests fail to detect extrapulmonary TB, requiring additional testing and increasing healthcare costs. In rural areas, the lack of skilled radiologists leads to inconsistent interpretations of chest X-rays, resulting in misdiagnosis or delayed treatment. TB diagnosis also suffers from high inter-reader variability, where radiologists may have differing opinions on the same X-ray, leading to diagnostic errors. Additionally, drug-resistant TB strains are more difficult to detect using conventional methods, further complicating treatment strategies. These limitations highlight the urgent need for an automated, high-accuracy TB detection system that can assist in timely diagnosis and reduce the burden on healthcare infrastructure.

2. LITERATURE SURVEY

In Iraq, one of the main causes of mortality is tuberculosis, with a rate of 9.24% per 100,000 inhabitants, according to data from the Statistical and Death System of the General Directorate of Epidemiology [1]. Y. Kurmi et al. they founded the use of image processing, pattern recognition, and artificial intelligence to help detect clusters of microcalcifications in digitized mammography images [2]. Pasa et al. proposed a deep network architecture with an accuracy of 86.82 percent for TB screening. Additionally, they demonstrated an interactive visualization application for patients with TB [3]. Chhikara et al. investigated whether CXR pictures might be used to detect pneumonia. They used preprocessing methods like filtering and gamma correction to evaluate the performance of pretrained models like Resnet, ImageNet, Xception, and Inception [4]. T Rahman et al. they proposed a Reliable TB Detection Using Chest X-ray with Deep Learning, Segmentation, and Visualization they used deep convolutional neural networks and the modules ResNet18, ResNet50, ResNet101, ChexNet, InceptionV3, Vgg19, DenseNet201, SqueezeNet, and MobileNet to differentiate between tuberculosis and normal images. In the identification of tuberculosis using X-ray images, the top-performing model, ChexNet, had accuracy, precision, sensitivity, F1-score, and specificity of 96.47 percent, 96.62 percent, 96.47 percent, 96.47 percent, and 96.51 percent, respectively [5].

S Kieu Tao et al. developed a deep learning model for TB diagnosis using chest X-rays; according to the data, the suggested ensemble method achieved the highest accuracy of 89.77 percent, sensitivity of 90.91 percent, and specificity of 88.64 percent [6]. Paul E et al. they are developed a CNN (convolutional neural networks) model are often employed for image categorization is a technique that is well suited for image categorization of issue. This method will aid in the rapid detection of tuberculosis from chest X-ray pictures [7]. Before the input is sent through a neural network, it handles data convolution, maximum pooling, and flattening. It works because the various weights are set up using various inputs. Once the data have passed through the hidden layers, weights are computed and assessed. Following input from the cost function, the network goes through a back propagation phase [8]. Xie et al. they focused on the detection of TB-infected areas or lesions using a region-based faster RCNN (Region-based Convolutional Neural Network) method. They employed a combination of three datasets: the Montgomery County dataset [9]. Sahlol et al. implemented a new hybrid network, Mobile Net-AEO, in which artificial ecosystem-based optimization (AEO) works as a feature selector, keeping the relevant features and discarding the redundant features that are generated by the CNN. They used a combination of two datasets, the Shenzhen Hospital dataset and the Mendeley Dataset (UK), which contains a total of 6,421 (3,883 TB and 2,538 normal) CXR images. Their study used a full dataset of 7,083 images (4,219 TB and 2,864 normal), which was split into training/test sets with a 80:20 ratios, and demonstrated an accuracy of 94.10% [10].

Rahman et al. they developed nine different transfer-learning-based deep neural networks, namely VGG19, ResNet18, ResNet50, ResNet101, MobileNet, DenseNet201, SqueezeNet, and ChexNet, to classify CXR images into normal and TB classes. Before classification, they segmented the lung region using a modified UNet network. They used a combination of four datasets: Montgomery, Shenzhen, Belarus TB Dataset (Belarus), and Radiological Society of North America Dataset (RSNA) [11].Guo et al. they developed a method averaging six deep neural networks, namely VGG16, VGG19, ResNet50, ResNet101, Inception V3, and ResNet34. Using the Shenzhen dataset with ten-fold cross-validation approach, they achieved an accuracy of 94.50% in their experiments [12].

Abideen et al. implemented a B-CNN (Bayesian-based CNN) method for the classification of CXR images into TB and normal classes. They used a combination of the Montgomery and Shenzhen datasets, giving a total of 800 CXR images with 394 TB and 406 normal images, which they split into training/test sets with an 80/20 ratio. They achieved an accuracy of 96.42% [13]. Ayaz et al. they used an ensemble model that combined hand-crafted features and DL features, with a Gabor filter to extract hand-crafted features and transfer-learning-based pre-trained networks to extract deep features. The pre-trained DL networks were Inceptionv3, MobileNet, Xception, ResNet50, and InceptionResnetv2 [14].

Rajaraman et al. used a bone-suppression-based ResNet-BS model to detects and remove occluding bony structures from CXRs, with a combination of the Montgomery and Shenzhen datasets. Their findings confirmed the better performance of DL classification models on bone-suppressed CXR images, with an accuracy of 92.30% and an AUC of 0.96 [15]. Acharya et al. they developed a normalization-free CNN and used it for classification of images into TB and normal classes. They used a combination of different datasets: the TBX11K (Tuberculosis X-ray) dataset, Shenzhen dataset, Montgomery dataset, Belarus, NIAID, SNA dataset, and the X-ray images dataset from the National Institute of Tuberculosis and Respiratory Diseases, New Delhi. This yielded a total of 8,688 CXR images with 4,936 TB and 3,752 normal images for their experiments. They demonstrated a classification accuracy of 96.91% with an AUC of 0.993 [16]. Zhou et al. they used a private dataset compiled from five different sources containing 4,856 CXR images (2,736 TB and 2,120 normal images). They used the UNet model to segment CXR images and achieved a Dice value of 0.958. After segmentation, they used the ResNet DL model to classify the segmented lung images into TB and normal classes. They achieved a classification accuracy of 94.8% with an AUC of 0.998 [17].

3. PROPOSED SYSTEM

Step 1: Dataset

The dataset consists of medical images categorized into two classes: Tumor (TB) and Normal. The dataset includes a total of 4200 images, with 700 images labeled as Tumor and 3500 labeled as Normal. This dataset serves as the foundation for building a binary classification model where the goal is to distinguish between tumor and normal conditions in medical scans.

Step 2: Dataset Preprocessing

Before training the model, the dataset undergoes preprocessing to ensure the quality of the input data. This step includes removing any **null values** that could potentially skew the model's learning process. Additionally, **label encoding** is performed to convert the categorical labels (Tumor, Normal) into numerical values, making them suitable for model training. Image resizing and normalization might also be applied to standardize the images for better model performance.

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Step 3: Existing Algorithm - Random Forest Classifier

The existing algorithm for classification is the **Random Forest classifier**. This ensemble machine learning method utilizes multiple decision trees to make predictions. Each tree is trained on a subset of the data, and the final prediction is made by aggregating the outputs of all the trees. Random Forest is known for its robustness in handling imbalanced datasets, but it may not perform as well as deep learning methods in image-based tasks like tumor detection in medical scans.

Step 4: Proposed Algorithm - Convolutional Neural Network (CNN)

The proposed algorithm is a Convolutional Neural Network (CNN), which is specifically designed for image classification tasks. CNNs are capable of automatically extracting features from images and are highly effective in medical image analysis. The model will consist of several convolutional layers, pooling layers, and fully connected layers to learn the spatial hierarchies and features of the medical images. This architecture is expected to outperform traditional machine learning methods, such as Random Forest, in terms of accuracy.

Step 5: Performance Comparison

Once both the Random Forest classifier and the CNN model have been trained, their performance will be compared. The evaluation will focus on metrics like accuracy, precision, recall, and F1-score. It is anticipated that the CNN model will yield higher accuracy in detecting tumors compared to the Random Forest classifier, as CNNs are tailored for handling image data and capturing complex patterns within medical images. This comparison will demonstrate the effectiveness of CNNs over traditional methods in the context of tumor detection in medical images.

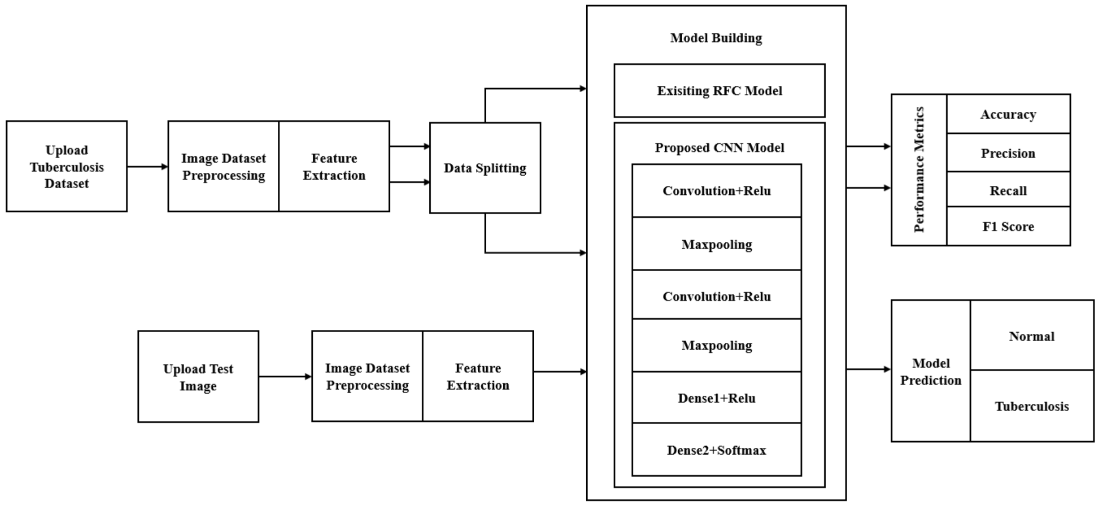

Fig. 1: Architectural Block Diagram of the Proposed System.

3.2 Data Splitting & preprocessing

Step 1: Data Splitting

The dataset, which contains 4200 images, is split into two main subsets:

1. **Training Set (80% of the dataset)**: This portion of the data is used to train the model. The model will learn the features of Tumor and Normal images by adjusting its weights based on this data.

2. **Test Set (20% of the dataset)**: This subset is kept aside for model evaluation. The test data is used to assess the model's generalization ability on unseen data.

Train-Test Split Method: A common approach is to use an **80-20 split**, meaning 80% of the data will be used for training and 20% for testing. This ensures that the model has enough data to learn from while also being evaluated on a separate portion to check for overfitting.

Step 2: Image Preprocessing

Image preprocessing is a critical step to enhance the input data quality and improve model performance. This involves several steps to ensure that the images are in the best format for training the model:

1. **Resizing**: All images are resized to a uniform size (e.g., 224x224 pixels) to maintain consistency. Neural networks require a fixed input size, and resizing ensures that the model can process images efficiently.
2. **Normalization**: Pixel values are typically normalized to fall within a specific range, usually between 0 and 1. This is done by dividing each pixel value by 255 (the maximum pixel value for an 8-bit image). Normalization helps the model converge faster during training and improves its performance.
3. **Augmentation (Optional)**: To increase the diversity of the training data and reduce overfitting, **image augmentation** techniques can be applied. This might include random rotations, flips, shifts, and brightness adjustments, which simulate various scenarios that the model may encounter in real-world situations.
4. **Label Encoding**: Since the dataset consists of categorical labels (Tumor or Normal), **label encoding** is used to convert these labels into numerical form. Typically, 'Tumor' might be represented as 1 and 'Normal' as 0, making it suitable for classification tasks.
5. **Data Shuffling**: The data is shuffled to ensure that the model is trained on a diverse set of images, avoiding any biases that could arise from the order in which images are presented.

3.3 ML Model Building

In the **ML Model Building** phase, the Random Forest classifier and CNN models are constructed to classify the images as either "Tumor" or "Normal." For the Random Forest model, we start by importing the necessary libraries and setting the number of decision trees (estimators) to a predefined value. The model is then trained using the training set with labeled images. For CNN, a deep learning model is built using layers such as Convolutional, Pooling, Flatten, and Dense layers. The architecture is carefully designed with filters for feature extraction, followed by fully connected layers for classification. Both models are trained using the preprocessed image data, with a focus on optimizing accuracy. Hyperparameters for both models (such as learning rate, batch size, etc.) are fine-tuned using cross-validation and grid search techniques. After training, both models are evaluated on the test set to determine their performance. The Random Forest model is typically evaluated using accuracy and F1 score, while the CNN model leverages performance metrics like accuracy, precision, recall, and loss. The best-performing model is selected for further analysis.

3.3.1 Proposed Algorithm: Convolutional Neural Networks (CNN):

Convolutional Neural Networks (CNNs) are widely regarded as the most effective approach for image classification, making them the ideal choice for this chest X-ray diagnostics project. CNNs excel in capturing spatial patterns within images by learning hierarchical features through multiple convolutional layers. Unlike Random Forest, CNNs are designed to process the spatial relationships in image data, which is critical for detecting subtle abnormalities in chest X-rays, such as tumors or pneumonia. CNNs can automatically learn from raw image data without the need for manual feature extraction, significantly improving accuracy by focusing on the most relevant features of the image. As the network learns from large datasets, CNNs adapt to the nuances of various diseases, offering higher generalization and robustness across different cases. Moreover, CNNs scale well with large volumes of data, enabling real-time analysis of chest X-rays in clinical settings. Their ability to detect complex, subtle patterns and generalize well to new data makes CNNs the most suitable algorithm for this project. In comparison to Random Forest, CNNs offer higher accuracy, faster processing times, and are better suited to the task of automated medical image analysis, contributing to more accurate and efficient diagnoses.

4. RESULTS

Dataset Composition:

- **Total Number of Images:** 4200 images
  - **Tumor (TB) Images:** 700 images (Tumor is the target class, representing positive detection)
  - **Normal Images:** 3500 images (Normal is the negative class, representing no tumor detected)

Class Distribution:

- **Class 0 (Normal):** 3500 images
- **Class 1 (Tumor):** 700 images

Image Format:

- Images are likely to be in formats such as **JPEG, PNG**, common for medical imaging.
- **Resolution:** The images could have varying resolutions, but for consistent processing, they might be resized to a standard size (e.g., 64x64, 128x128, or 224x224 pixels) during preprocessing.

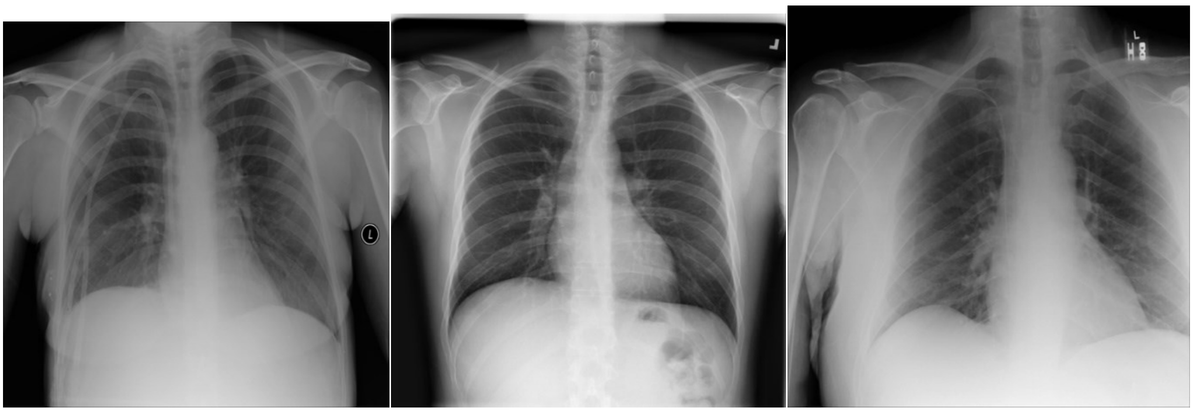

Figure 2: Normal X-ray images.

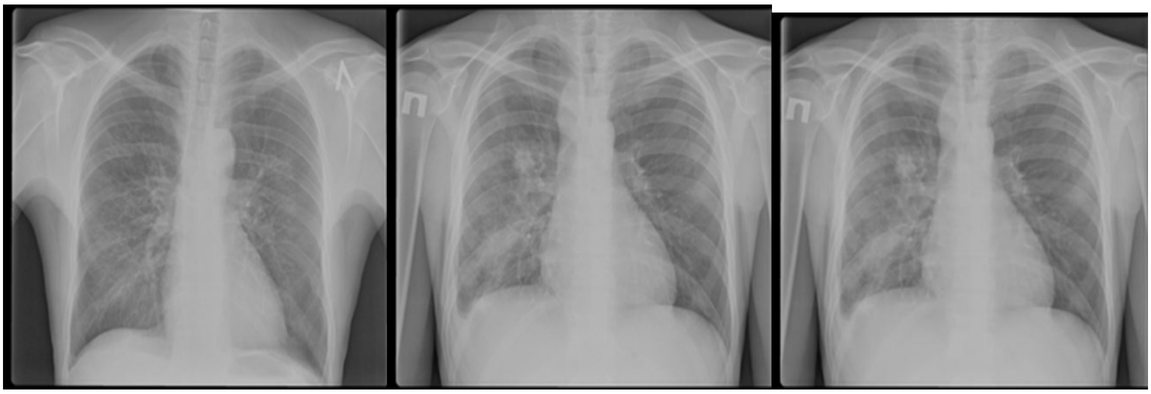

Figure 3: Tuberculosis X-ray images.

Figure 4 represents the first step in the GUI interface, where the user uploads the tuberculosis dataset. The interface allows the user to select the dataset folder, which contains images of two classes: Normal and Tuberculosis. After the dataset is uploaded, the GUI displays the available classes, enabling the user to confirm that the dataset contains the correct labels for classification. This stage is crucial in understanding the structure of the dataset, which is used for model training and evaluation.

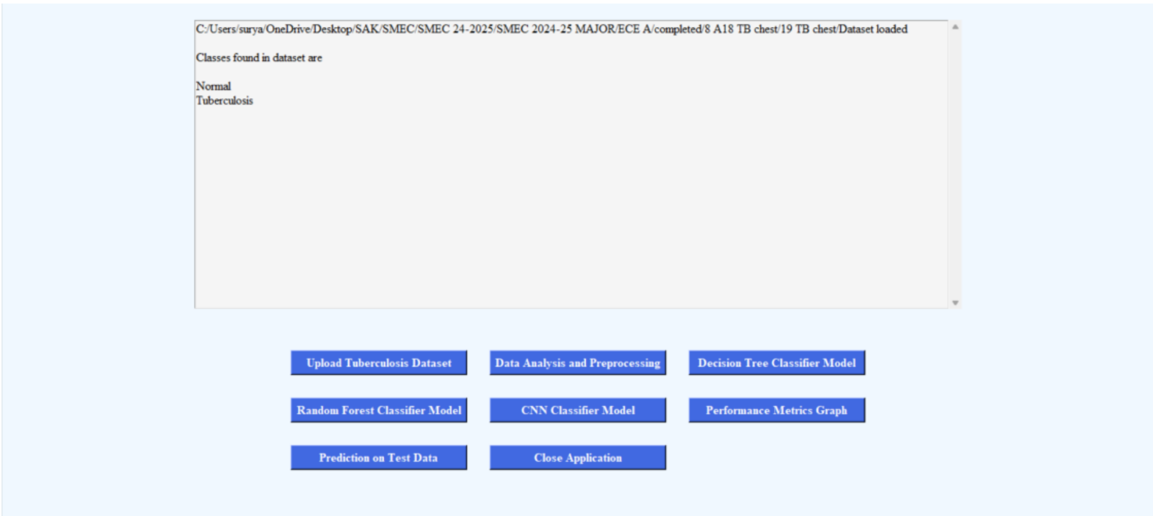

Figure 4: Upload of Tuberculosis Dataset and Its Analysis in the GUI Interface

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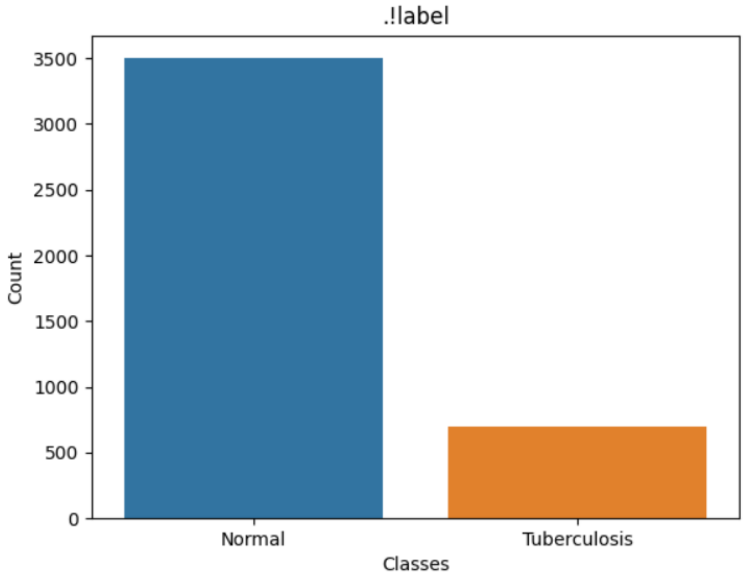

Figure 5: Image Preprocessing in the GUI

Figure 5 shows the preprocessing stage of the uploaded dataset. This process includes resizing images to a fixed size (64x64 pixels) and flattening them for the models. The images are processed into a numerical format, which is then used as input to machine learning models like the Decision Tree Classifier, Random Forest Classifier, and Convolutional Neural Network. Proper image preprocessing ensures that the models receive consistent and standardized data, improving their ability to classify images accurately.

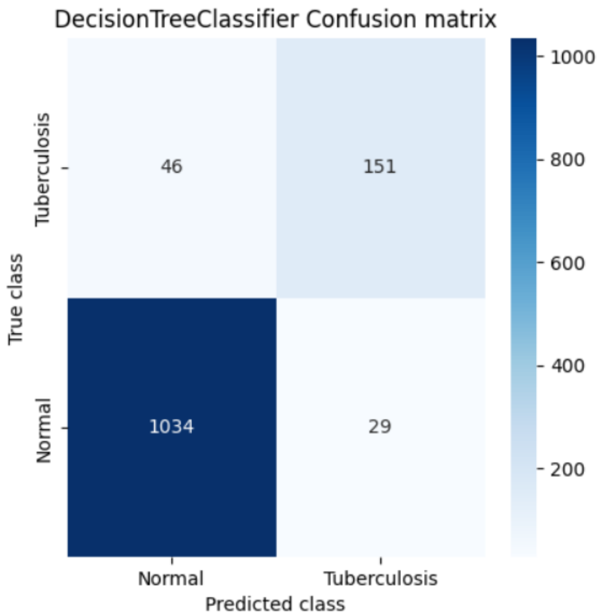

Figure 6: Performance Metrics and Confusion Matrix Plot of the DTC Classifier Model

Figure 6 presents the performance metrics for the Decision Tree Classifier model. The metrics, including Accuracy (94.05%), Precision (89.81%), Recall (86.96%), and F1-Score (88.30%), indicate that the DTC model performs well, though its precision and recall values for detecting tuberculosis are lower than those of the other models. The Confusion Matrix displayed here provides insight into the number of true positives, true negatives, false positives, and false negatives. The DTC model achieves high accuracy for classifying the "Normal" class, but it shows slightly lower performance in predicting the Tuberculosis class, as evidenced by the F1-Score and recall. This model's confusion matrix reveals more false negatives for Tuberculosis compared to Normal.

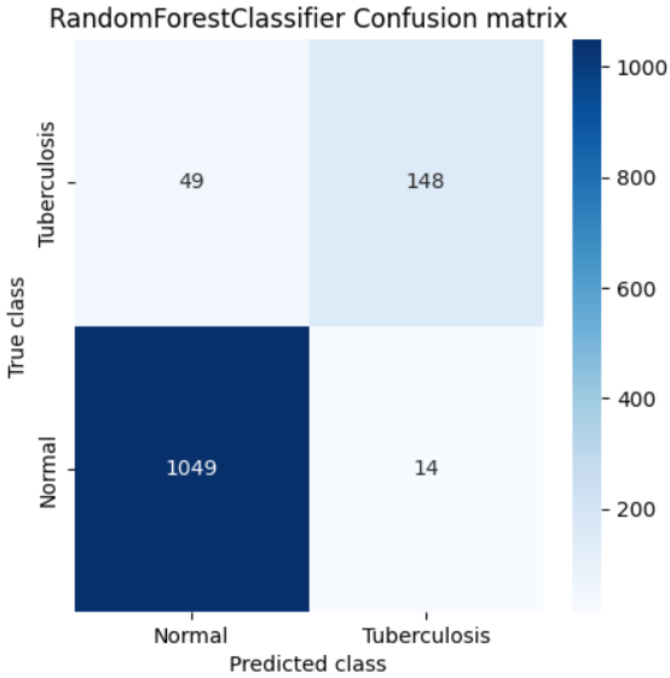

Figure 7: Performance Metrics and Confusion Matrix Plot of the RFC Classifier Model

Figure 7 displays the performance of the Random Forest Classifier model. The RFC model demonstrates Accuracy (95.00%), Precision (93.45%), Recall (86.90%), and F1-Score (89.77%), which are an improvement over the DTC Classifier. It achieves a slightly higher accuracy, with a notable increase in Precision, which means the RFC model is more precise when identifying the Normal class. However, the recall for Tuberculosis remains similar to the DTC model, indicating some challenges in accurately identifying Tuberculosis instances. The Confusion Matrix shows a better distribution of predictions compared to the DTC model, but there is still a performance gap when detecting the Tuberculosis class, as evident by the Recall and F1-Score.

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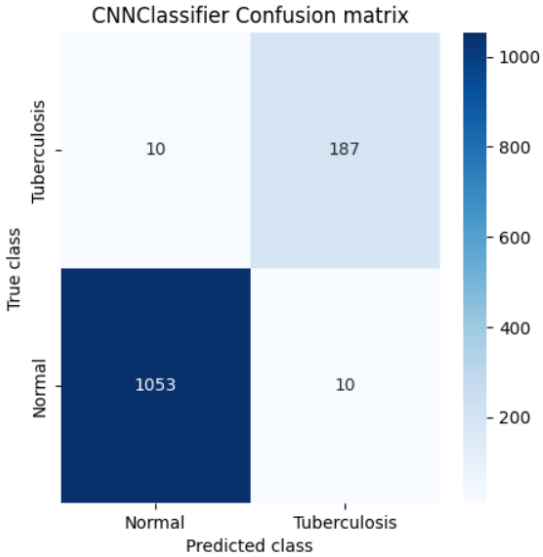
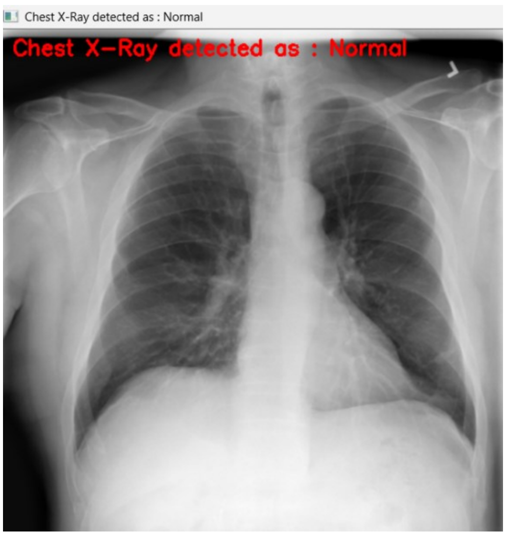


Figure 8: Performance Metrics and Confusion Matrix Plot of the CNN Classifier Model

In Figure 8, the Convolutional Neural Network (CNN) Classifier model outperforms the DTC and RFC models. With Accuracy (98.41%), Precision (96.99%), Recall (96.99%), and F1-Score (96.99%), the CNN model demonstrates its effectiveness in classifying Normal and Tuberculosis classes with high accuracy. The Confusion Matrix for the CNN model shows an excellent classification performance with fewer false positives and false negatives, especially for the Tuberculosis class. The F1-Score for Tuberculosis (96.99%) and Normal (99%) reflects the model's balanced performance in both categories.



Test Case Data 1

Test Case Data 2

Figure 9: Model Prediction on Test Cases.

Figure 9 illustrates the prediction of the trained model on a test image, demonstrating the model's ability to predict whether an image belongs to the Normal or Tuberculosis class. The predicted label is displayed on the image, showing the Tuberculosis prediction result in the GUI interface. This step allows users to visually confirm the accuracy of the model by testing it with new, unseen data.

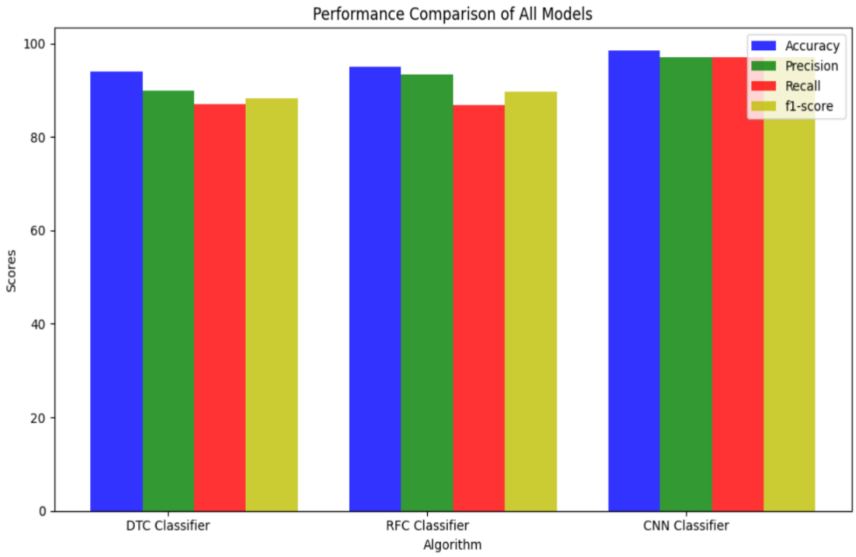


Figure 10: Performance comparison graph of models.

Figure 10 compares the performance of the three models: Decision Tree Classifier (DTC), Random Forest Classifier (RFC), and CNN Classifier. The graph presents a visual comparison of Accuracy, Precision, Recall, and F1-Score for each model, highlighting that the CNN Classifier outperforms the other models in every metric. The graph serves as an intuitive way for users to compare the effectiveness of the models for tuberculosis classification and helps in selecting the best-performing model for deployment.

Table 1: Performance metrics of all models.

Algorithm Name	Accuracy	Precision	Recall	F1-Score
DTC Classifier	94.05%	89.81%	86.96%	88.30%
RFC Classifier	95.00%	93.45%	86.90%	89.77%
CNN Classifier	98.41%	96.99%	96.99%	96.99%

Table 1 presents the performance metrics of three classification models: Decision Tree Classifier (DTC), Random Forest Classifier (RFC), and Convolutional Neural Network (CNN) Classifier. The table includes the accuracy, precision, recall, and F1-score for each algorithm. The CNN Classifier outperforms both the DTC and RFC models in all metrics, demonstrating the superior performance of deep learning for tuberculosis classification based on image data

5. CONCLUSION

This research successfully developed and evaluated machine learning models for the detection of tuberculosis from image data. Among the models tested, the Convolutional Neural Network (CNN) outperformed both the Decision Tree Classifier (DTC) and Random Forest Classifier (RFC), achieving the highest accuracy and balanced precision-recall values. The CNN demonstrated an accuracy of 98.41%, making it the most effective model for this task. The Random Forest model, while effective, performed slightly lower in comparison, with 95% accuracy, and the Decision Tree model had the lowest performance. These results demonstrate the potential of deep learning techniques, particularly CNN, for effective tuberculosis detection and classification, offering significant promise for real-world applications in healthcare, where quick and accurate diagnoses are critical.

REFERENCES

[1] R. S. Radhwan and F. S. Al-Nasiri, Detection of infection with hydatid cysts in abattoirs animals at Kirkuk governorate, Iraq, Tikrit Journal of Pure Science, vol. 26, no. 4, pp. 24–32, 2021.

[2] Y. Kurmi, V. Chaurasia, A. Goel, D. Joshi, and N. Kapoor, Tuberculosis bacteria analysis in acid fast stained images of sputum smear, Signal, Image and Video Processing, vol. 15, no. 1, pp. 175–183, 2021.

[3] Pasa F., Golkov V., Pfeiffer F., Cremers D, Pfeiffer D. Efficient deep network architectures for fast chest X-ray Tuberculosis screening and visualization. Scientific Reports 2019;9(1):6268–6269. doi: 10.1038/s41598-019-42557-4.

[4] Chhikara P., Singh P., Gupta P., Bhatia T. Deep convolutional neural network with transfer learning for detecting Pneumonia on Chest X-rays. Advances in Intelligent Systems and Computing. 2019; 1064:155–168. doi: 10.1007/978-981-15-0339-9_13.

[5] Rahman T., Khandakar A., Kadir M. A., et al. Reliable Tuberculosis detection using chest X-ray with deep learning, segmentation and visualization. IEEE Access.2020;8:191586–191601. doi: 10.1109/ACCESS.2020.3031384.

[6] Kieu S., Hwa T., Hijazi M. H. A., Bade A., Yaakob R., Jeffree M. S. Ensemble deep learning for tuberculosis detection using chest X-ray and canny edge detected images. IAES International Journal of Artificial Intelligence 2019;8(4):429–435. doi: 10.11591/ijai.v8.i4.pp429-435.

[7] Paul E., Gowsalya P., Devadarshini N., Indhumathi M. P., Iniyadharshini M. Plant leaf perception using convolutional neural network. International Journal of Psychosocial Rehabilitation. 2020;24(5):5753–5762. doi: 10.37200/ijpr/v24i5/pr2020283.

[8] Sarıgül M., Ozyildirim B. M, Avci M. Differential convolutional neural network. Neural Networks: The Official Journal of the International Neural Network Society 2019;116(9):279–287. doi: 10.1016/j.neunet.2019.04.025.

[9] Y Xie, Z Wu, X Han, et al. Computer-aided system for the detection of multicategory pulmonary tuberculosis in radiographs J Healthc Eng, 2020 (2020), Article 9205082.

[10] A T Sahlol, M Abd Elaziz, A Tariq Jamal, et al. A novel method for detection of tuberculosis in chest radiographs using artificial ecosystem-based optimisation of deep neural network features Symmetry, 12 (7) (2020), p. 1146, doi:10.3390/sym12071146.

[11] T Rahman, A Khandakar, MA Kadir, *et al.* Reliable tuberculosis detection using chest X-ray with deep learning, segmentation and visualization IEEE Access, 8 (2020), pp. 191586-191601, doi :10.1109/access.2020.3031384.

[12] R Guo, K Passi, CK. Jain Tuberculosis diagnostics and localization in chest X-rays via deep learning models Front Artif Intell, 3 (2020), Article 583427, doi:-10.3389/frai.2020.583427.

[13] Z Abideen, M Ghafoor, K Munir, et al. Uncertainty assisted robust tuberculosis identification with Bayesian convolutional neural networks IEEE Access, 8 (2020), pp. 22812-22825, doi: 10.1109/ACCESS.2020.2970023.

[14] M Ayaz, F Shaukat, G. Raja Ensemble learning based automatic detection of tuberculosis in chest X-ray images using hybrid feature descriptors Phys Eng Sci Med, 44 (1) (2021), pp. 183-194, doi:- 10.1007/s13246-020-00966-0.

[15] S Rajaraman, G Zamzmi, L Folio, et al. Chest X-ray bone suppression for improving classification of tuberculosis-consistent findings Diagnostics, 11 (5) (2021), p. 840, 10.3390/diagnostics11050840.

[16] V Acharya, G Dhiman, K Prakasha, et al. AI-assisted tuberculosis detection and classification from chest X-rays using a deep learning normalization-free network model Comput Intel Neurosc, 2022 (2022), pp. 1-19, doi:- 10.1155/2022/2399428.

[17] W Zhou, G Cheng, Z Zhang, et al. Deep learning-based pulmonary tuberculosis automated detection on chest radiography: large-scale independent testing Quant Imaging Med Surg, 12 (4) (2022), pp. 2344-2355,doi:- 10.21037/qims-21-676.