DETECTION OF TUBERCULOSIS, COVID-19, PNEUMONIA USING IMAGE PROCESSING

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ABSTRACT

Chest X-rays are crucial in diagnosing lung disorders, and radiologists play a major role in pneumonia detection. Autonomous systems in remote areas enhance treatment accessibility. This article delves into the application of deep learning for COVID-19, pneumonia, and tuberculosis identification in chest X-rays. Harnessing CNN (Convolutional Neural Networks) using Adam optimizer, our custom model extracts features and employs a classifier. Results underscore the efficacy of our approach, particularly in illness identification. Evaluation metrics including accuracy, precision, recall, and F-1 score are presented. This research underscores the capability of the custom CNN model in deep learning for accurate chest X-ray classification, promising improved diagnostic capabilities and timely interventions in respiratory illnesses.

Keywords: - *COVID-19, Tuberculosis, Pneumonia, CNN, Deep learning, Chest X-ray, Adam optimizer*

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1. INTRODUCTION

These days we've seen that respiratory illnesses including COVID-19, pneumonia, and tuberculosis present serious threats to global health. COVID-19, stemming from the novel coronavirus SARS-CoV-2, surfaced towards the end of 2019 [1,2,9], swiftly escalating into a worldwide pandemic. Regarding pneumonia [3], approximately 200 million cases are reported annually. According to [11] India holds the unfortunate distinction of having the highest number of pneumonia-related deaths globally, comprising approximately 20% of the total mortality among children under the age of five. It's approximated that a quarter of the global population carries Mycobacterium tuberculosis, with a lifetime risk of 5-10% for Tuberculosis [4] disease progression. WHO estimated that over a 10.6 million people are affected by Tuberculosis in 2021.[10] Rapid and accurate disease identification is essential for effective therapy. We mostly employ medical imaging such as X-rays CT scans MRI images etc… to detect these disorders. The internal structure of the lungs is mostly visualized using these images. These conventional techniques could take a long time and the outcome depends on the interpretation of the specialist or radiologist, thus to extract the crucial information from the X-ray images, image processing techniques are employed.

In this project, we will train and test a proprietary convolution neural network CNN model to determine if the patient has COVID-19 pneumonia or tuberculosis in addition to facilitating quick disease diagnosis this automatic detection lessens the load on the healthcare system. we see an era where automated disease identification will enhance global healthcare through advances in image processing this article discusses the automated disease identification of

COVID-19 pneumonia tuberculosis and normal chest X-rays using CNN convolution neural network and image processing.

2. EXISTING METHODS

S. Wang, B. Kang, J. L. Ma, X. Zeng, M. Xiao, J. Guo, M. Cai, J. Yang, Y. li, X. Meng and B. Xu proposed a project named "A deep learning algorithm using CT images to screen for Coronavirus disease (COVID-19)" [5]. They have done this project based on the radiographic changes in CT images. They have collected a total of 1065 CT images. They have used the inception v3 transfer learning model to establish the algorithm and have achieved a testing accuracy of 79.3%, and a validation accuracy of 89.5% They have trained the model for 15,000 epochs with an initial learning rate of 0.01

XiaoQing Zhang', 'GuangYu Wang' and 'Shu-Guang Zhao' proposed a project named "CapsNet covid-19 model: Lung CT (Computed Tomography) image classification method based on the CapsNet model [6]. This system was published in the year 2022 when the outbreak of the coronavirus disease 2019 (COVID-19) posed a serious threat to human health and life around the world. In this existing system, these authors used CT images of the lungs to find out whether the patient has 'COVID-19' or 'pneumonia' or is a normal CT image. They have used the CapsNet model to study the data (which includes several lung CT images of COVID-19, general pneumonia, and normal lung CT images in the 2019 Novel Coronavirus Information Database) of 29278 images and classify them into 'covid-19', 'pneumonia', and normal CT images. They have achieved a training accuracy of 100%, testing accuracy of 84.291%, precision of 76.9%, Recall rate of 96.4%, and F1 score of 84.2%.

N. Sonti, R. M. S. S, and V. R. P., proposed "COVID-19 Detection from X-rays using CNN-based Graph with Fast Localization spectral filters,"[7] in 2023. They used a deep learning-based method CNN-GFL which showcases swift training capabilities, facilitating expedited and precise predictions of COVID-19 with high accuracy. Their innovative utilization of spectral filters within the CNN-GFL framework showcases not only efficiency but also robustness in identifying COVID-19 cases from X-ray images.

Jain, R., Nagrath, P., Kataria, G., Kaushik, V. S., & Hemanth, D. J. proposed "Pneumonia detection in chest X-ray images using convolutional neural networks and transfer learning"[8]. The paper introduces Convolutional Neural Network (CNN) models for pneumonia detection using X-ray images. Six models, including both custom and pre-trained architectures like VGG16, VGG19, ResNet50, and Inception-v3, were trained and evaluated. The results demonstrate promising accuracy rates, with the best-performing model achieving a validation accuracy of 92.31%.

The aforementioned models focus on detecting either one or two diseases, with relatively lower accuracy and metric values. Also [6] achieved a training accuracy which is a case of overfitting. Therefore, we propose a deep-learning CNN model capable of detecting three diseases: pneumonia, tuberculosis, and COVID-19. This model aims to achieve higher accuracy and improved performance metrics by incorporating four classifications, including normal X-ray images.

3. DATASET

We've compiled a dataset comprising 4670 X-ray images from Kaggle, divided into 3736 training and 934 testing images at an 80:20 ratio. The dataset encompasses four categories: pneumonia, tuberculosis, COVID-19, and normal cases. Each image is meticulously labeled, enabling nuanced diagnosis and machine learning model training. Rigorous preprocessing ensures standardized image quality, while efforts to incorporate diverse demographics and clinical scenarios enhance the dataset's representativeness. This resource equips healthcare professionals with accurate diagnostic tools, ultimately aiming to improve patient outcomes. Regular updates and contributions from the research community ensure the dataset remains dynamic and applicable to evolving diagnostic challenges. By fostering advancements in medical imaging analysis and respiratory disease detection, this dataset contributes significantly to healthcare innovation and patient care. Fig -1 shows the various categories of classifications present in the dataset.

(a) (b) (c) (d)

Fig -1: Categories of Chest X-ray images (a) COVID-19 (b) Tuberculosis (c) Pneumonia (d) Normal

4. PROPOSED WORK

In the proposed system, a custom CNN model is developed to address the low accuracy and performance metrics associated with classifying COVID-19, pneumonia, tuberculosis, and normal cases in X-ray images. To enhance accuracy, the CNN architecture will be meticulously designed, taking into account the specific characteristics and complexities of the dataset. Various architectural choices such as the number of layers, kernel sizes, activation functions, and regularization techniques will be explored to optimize the model's performance. Additionally, data augmentation techniques will be applied to artificially expand the training dataset, enabling the model to learn from a more diverse set of examples and improve generalization. Furthermore, hyperparameter tuning will be conducted to fine-tune the model's parameters and optimize its performance on the validation set. By leveraging a custom CNN architecture tailored to the dataset, the proposed system aims to achieve significant improvements in accuracy and performance metrics, thereby enhancing the reliability of respiratory disease diagnosis. Fig -2 represents the block diagram of our proposed work and it is explained.

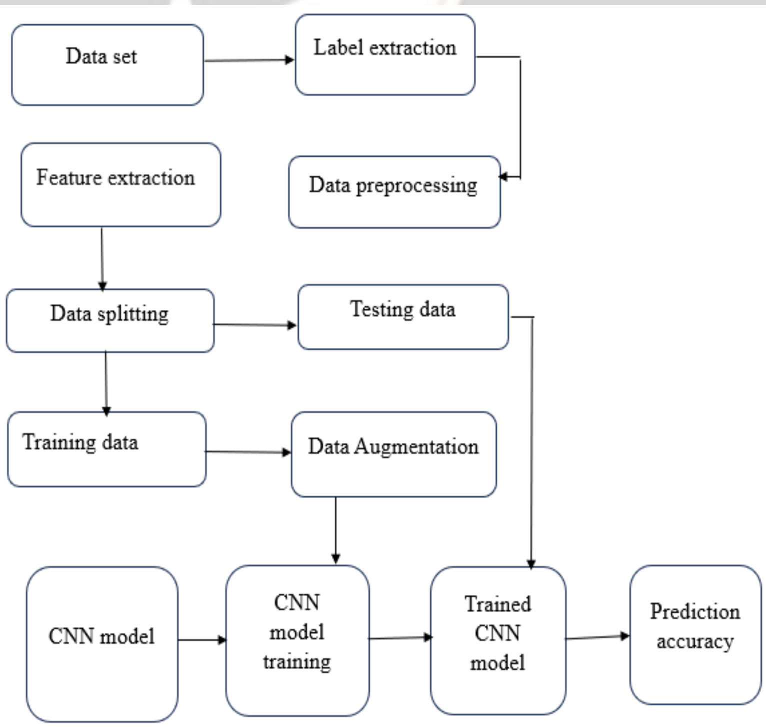

Fig -2: Block diagram

4.1 Label extraction:

In the label extraction step, each image in the dataset needs to be associated with the corresponding label. In this project, as we have four classifications each image will be associated with any of the four labels that are pneumonia, tuberculosis, COVID-19, and normal.

4.2 Feature extraction:

In the feature extraction step important features like edges, corners, textures, etc… are extracted from the images.

4.3 Data preprocessing:

Real-world data often comes in messy formats which is not suitable for training a model straight away. Data processing involves image cleaning, image resizing, image normalization, etc… we are resizing the image into 224*224 for both input and output formats.

4.4 Data splitting and data augmentation:

This pre-processed data is split into training and testing sets maintaining a balanced label distribution. In the training dataset, we may have imbalanced data which may lead to low performance. So, for better performance of the model, we performed data augmentation on the training data where the images will undergo rotation, flipping, and shifting to balance the dataset.

5. DESIGN METHODOLOGY OF CNN

For training the system we made use of custom Convolutional Neural Networks (CNN) model. The model we have built using CNN architecture consists of four Convolutional layers, a Batch Normalization layer, and a ReLU activation layer followed by each of the four convolutional layers. After that, there is an addition layer, an Average pooling layer, a Fully connected layer, a softMax layer, and a classification layer. In the proposed work we achieved more accuracy than the existing models. We trained our model using the Adam optimizer for 35 epochs with a mini-batch size of 32 and learning of 1e-4. Fig -3 represents the architecture of the CNN model.

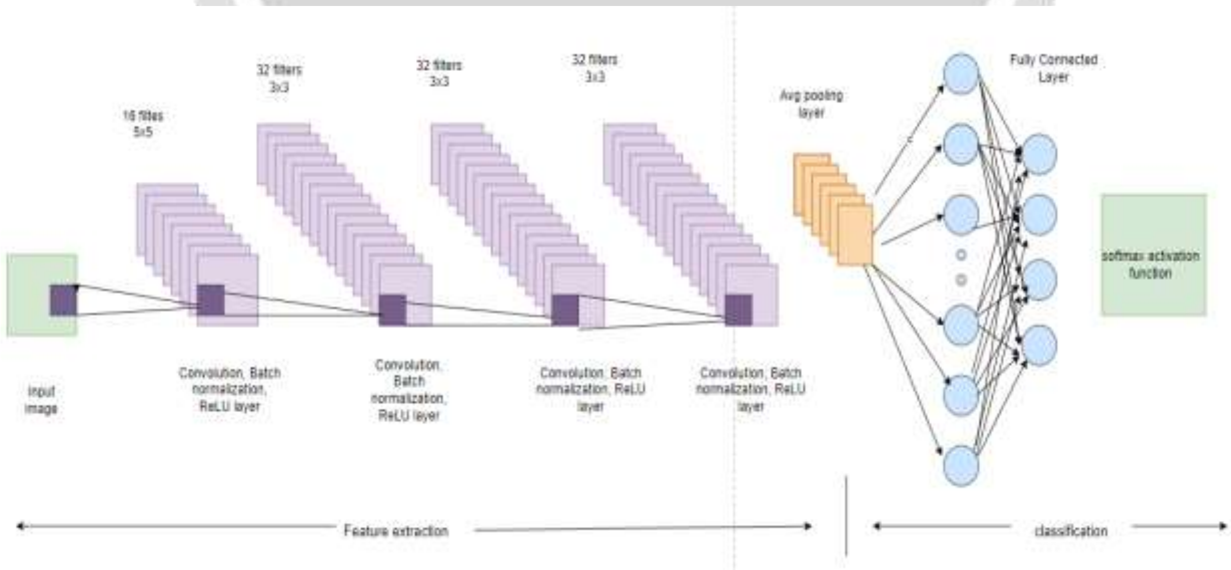

Fig -3: CNN architecture

5.1 Convolution layer:

In this CNN model, we used 4 convolution layers with the number of filters (known as kernel) ranging from 16 to 32 and the size of filters ranging from 3*3 to 5*5. Immediately after every convolution layer we used a batch normalization layer, and an activation layer (ReLU activation function). These layers play a very important role in extracting the spatial patterns like edges, lines, and textures which are vital in training the CNN model.

Let X be the input tensor to the convolutional layer, Y be the output tensor of the convolutional layer, W be the weight tensor of the convolutional layer, b be the bias vector of the convolutional layer, P be the padding. S denotes the stride.

$$Y_{\mathrm{i,\,j,\,k}} = \sum_{p=0}^{F_1-1} \sum_{q=0}^{F_2-1} \sum_{r=0}^{C_{\mathrm{in}}-1} W_{\mathrm{p,\,q,\,r,\,k}} \,.\, P_{(i\times S+p-P_1),(j\times S+q-P_2),r} + b_{\mathrm{k}}$$

5.2 Average Pooling Layer:

In this model, we have used an average pooling layer with a pooling window size of 4*4 and a stride of 3. The average pooling layer is used to minimize the spatial dimensions in the input image preserving the important features. This layer computes the average of each pooling window over the feature map.

Let X be the input tensor, Y be the output tensor of the average pooling layer, K be the pool size and S be the stride. The output equation of the average pooling layer is as follows.

$$Y_{\mathrm{i,\,j,\,k}} = \left(\frac{1}{k^2}\right) \sum_{p=0}^{k-1} \sum_{q=0}^{k-1} X_{(i\times S+p),(j\times S+q),k}$$

5.3 Fully connected layer and softmax layer:

A fully connected layer is used to connect every neuron of the previous layer (average pooling layer) to every neuron of its layer which enables to capture of the complex patterns and relationships in input data which will help the model to learn high-level features and make predictions.

The softmax layer is generally an output layer in the classification tasks. The softmax layer will convert the raw output values from the previous layer into probabilities of each class.
Let X be the input vector, y be the output vector, and N is the number of elements in the input vector. The mathematical equation of the softmax layer is followed as:

$$Y_{\mathrm{i}} = \left(\frac{e^{x_i}}{\sum_{j=1}^{N} e^{x_j}}\right)$$

6. EXPERIMENT AND RESULT

We have done the project in the MATLAB 2021 version. We used MATLAB toolboxes such as:

- Image processing toolbox
- Deep learning toolbox

6.1 Image processing toolbox:

This toolbox is used for handling and processing images. Functions from this toolbox are used for tasks like reading images, performing image preprocessing, and visualization. From the image processing toolbox, functions like imageDatastore, countEachLabel, splitEachLabel, and Data augmentation are used.

6.2 Deep learning toolbox:

The deep learning toolbox provides functions and tools for designing, training, and analyzing deep neural networks. From the deep learning toolbox functions like Layergraph, CNN layers, trainingOptions, trainNetwork, and classify are used.

Following 35 consecutive epochs of training, the CNN model demonstrated significant progress, achieving a training accuracy of 96.88%, a validation accuracy of 95.41%, and an impressive testing accuracy of 98.7% in marking a single image. Visualized through accuracy and loss plots, the model's performance on the training set is evident. These results indicate robust learning and effective generalization capabilities, highlighting the model's proficiency in classification tasks. The following table depicts the accuracy and loss for training and validation.

Table -1: Accuracy and Loss

Values	Training	Validation
Accuracy	96.88%	95.41%
Loss	0.1035	0.1520

Table -2: Evaluation metrics of four classes

Class	Precision	Recall rate	F-1 Score
COVID-19 (Class-0)	0.92	1.0	0.9583
Normal (Class-1)	0.8611	0.9841	0.9182
Pneumonia (Class-2)	0.9938	0.9415	0.9669
Tuberculosis (Class-3)	1.0	0.9230	0.96

Accuracy = $\frac{\mathrm{TP+TN}}{\mathrm{TP+TN+FP+FN}}$

Precision = $\frac{\mathrm{TP}}{\mathrm{TP+FP}}$

Recall = $\frac{\mathrm{TP}}{\mathrm{TP+FN}}$

F1-Score = 2*$\frac{(Precision*Recall)}{(Precision+Recall)}$

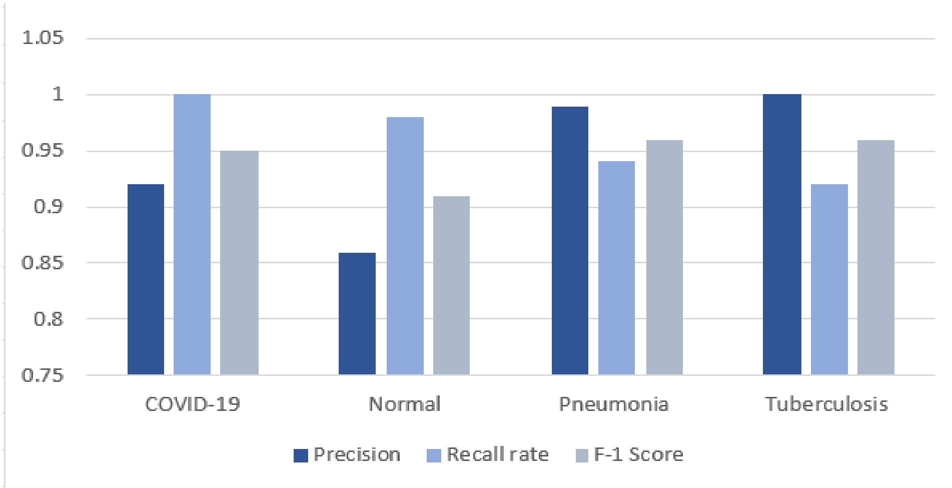

Chart -1: Bar chart of classes vs metrics values

Fig -4 illustrates the training plot, showcasing the relationship between accuracy and iteration count, as well as the variation in loss over iterations. Each epoch comprises 81 iterations. Additionally, the figure includes the validation accuracy, offering insights into model performance beyond the training data.

Fig -4: Training plot iteration vs accuracy and iteration vs loss

The following figure is the confusion matrix of four classifications from which we can calculate the performance metrics. The four classifications are COVID -19, Pneumonia, Tuberculosis and normal.

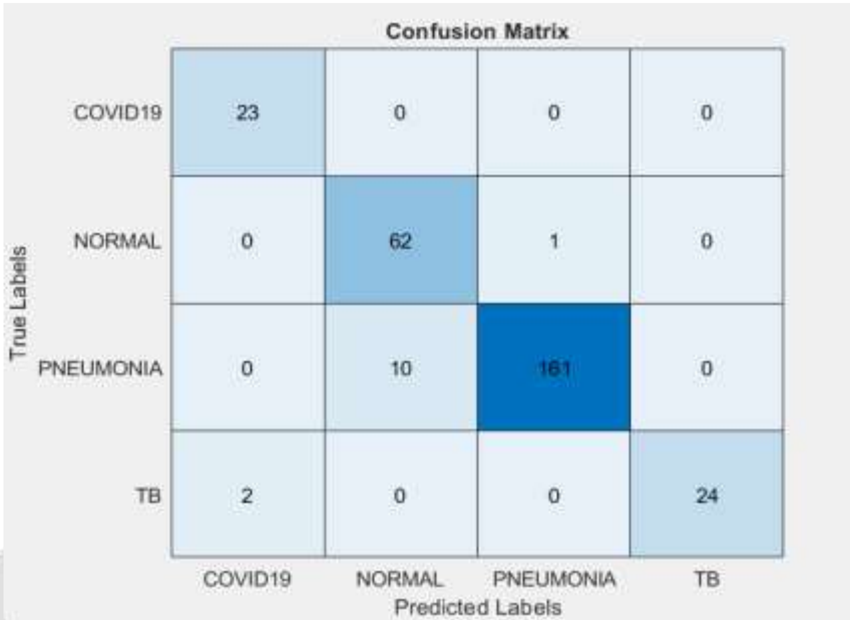

Fig-5: Confusion Matrix

After training is completed, the model will randomly select any four images from the dataset along with their confidence score. It represents the model's certainty about its predictions. It's a probability measure indicating how confident the model is in its output.

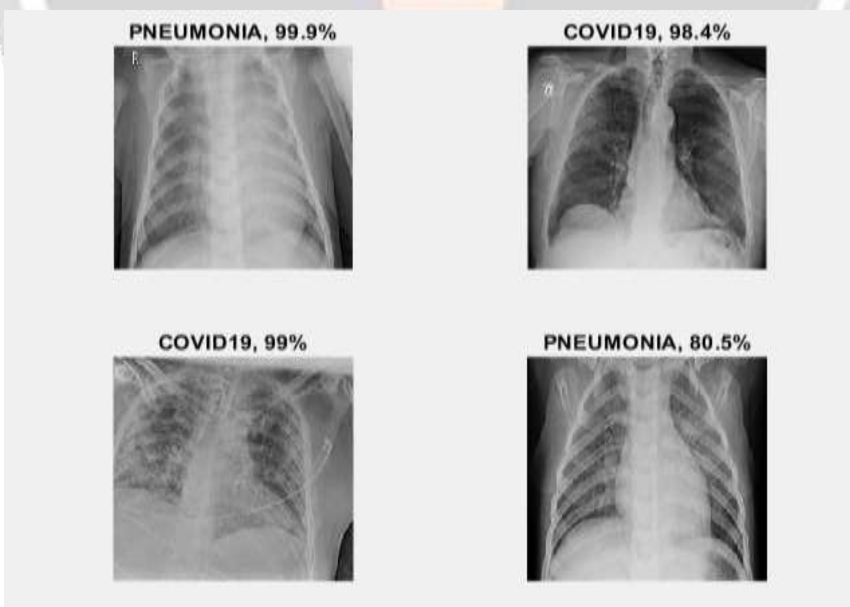

Fig-6: Random images from the dataset with Confidence Score

Following the training of the CNN model, we'll input images to evaluate its accuracy in identifying COVID-19, pneumonia, tuberculosis, or normal cases. Based on the input, the model will provide corresponding outputs.

Table -3: Accuracy comparision between existing and proposed model

Model	Training accuracy	Validation accuracy	classifications
CNN (proposed)	96.88%	95.41%	COVID-19, Normal, pneumonia, Tuberculosis
Reference [5]	89.5%	79.3%	COVID-19, Normal,
Reference [6]	100%	84.291%	COVID-19, Normal, pneumonia
Reference [8]	-	92.31%	Normal, pneumonia

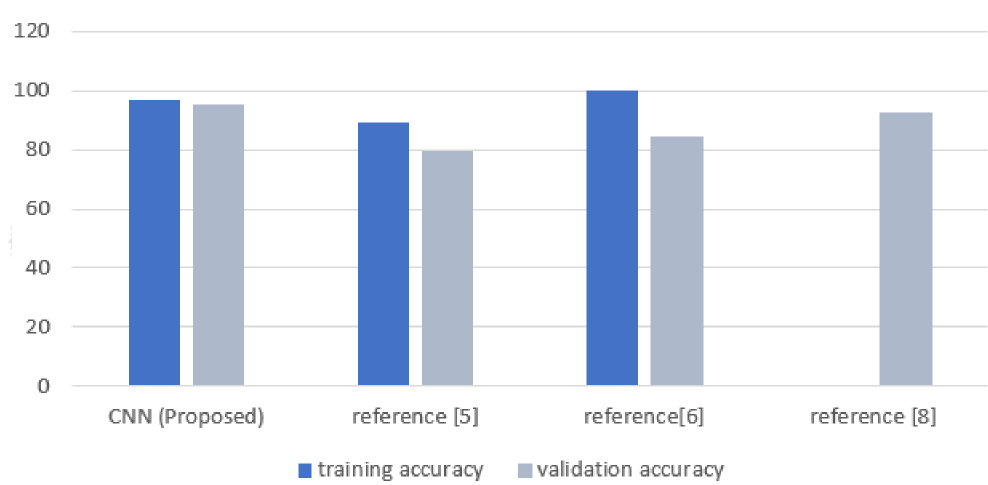

Chart-2: Bar chart of model and their accuracy values

7. CONCLUSION

In conclusion, this project demonstrates the potential of image-processing techniques in aiding the diagnosis of critical respiratory diseases such as COVID-19, pneumonia, and tuberculosis. Through the utilization of advanced algorithms and machine learning models, accurate and timely detection of these diseases can be achieved, facilitating prompt medical intervention and improving patient outcomes. The results obtained from this study highlight the effectiveness of employing image analysis methods for medical purposes, showcasing their ability to complement traditional diagnostic approaches. However, further research and refinement are necessary to enhance the robustness and scalability of these techniques for widespread clinical adoption. Overall, this project underscores the promising role of technology in revolutionizing healthcare delivery and advancing the fight against infectious diseases.

8. REFERENCES

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