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Anomaly Detection in Chest X-ray Images and Classifying Disease using Deep Learning models

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Abstract

In this research we have explored effectiveness of autoencoder in anomalous detection, deep learning models in image classification and Grad-CAM in Explanation of classification and detection. We mainly focused on classifying Tuberculosis and Pneumonia. We collected normal, Tuberculosis and Pneumonia chest X-ray images from publicly available Kaggle dataset. Our research constitutes of two stages. In stage 1, We trained Autoencoder on only one class i.e., normal chest X-ray images. Thus, making the model more effective in detecting anomaly in a chest X-ray image if it is having anomalous pattern compared to normal image. If the model detects any anomaly it is directed to stage 2 where the deep learning models i.e., InceptionV3 and Xception are trained on Tuberculosis and Pneumonia chest X-ray images. These models are integrated with Grad-CAM to generate heatmap that detects and visualizes disease spot in the test image. These models are evaluated on training and testing accuracies. Xception model has achieved an accuracy of 100 % while InceptionV3 achieved an accuracy of 99.77%. The Integration of Grad-CAM made it easier to interpret and trust the model's decision-making process.

Key words: InceptionV3, Xception, Autoencoder, Grad-CAM

1. Introduction

In today's world Tuberculosis (TB) and Pneumonia are some of the deadliest diseases causing millions of deaths annually despite advancements in medical science. According to the World Health Organization, approximately 3.5 million people pass away annually due to Tuberculosis and Pneumonia collectively. These diseases are caused irrespective of age. Children under 5 years of age and old age people above 60 years are more vulnerable to these diseases as they have weak immune systems.

The traditional diagnosis of these respiratory diseases heavily depends on chest X-ray examination by skilled radiologists and pulmonologists. These medical professionals are heavily trained in identifying the abnormalities in chest X-rays. Firstly, there is a significant global shortage of qualified professionals to identify these diseases, especially in rural areas where these diseases are common. Interpretation of X-rays by these professionals can be subject to fatigue-related errors, inter-observer variability, and limitations in detecting precise early-stage indications of these diseases. Early detection of these diseases plays a crucial role in improving patient's health from both Tuberculosis and Pneumonia. However, completely depending only on these professionals can slow down the diagnostic process delaying important decision-making for treatment.

In recent days the emergence of Artificial Intelligence, Machine Learning and Deep Learning technologies has shown promising solutions to address these challenges. These computational approaches have several advantages over traditional diagnostic methods. Particularly deep learning models have shown remarkable capabilities in image recognition and detection outperforming humans in their specific fields. These models are trained on vast amount of image data and can detect the subtle patterns which human experts feel challenging in identifying. AI systems can help doctors by giving quick first checks and pointing out problem areas for them to look at more closely. Working together, AI and doctors can make diagnosis faster and more accurate. Using AI for chest X-ray analysis can be especially helpful in places with fewer medical resources, as it can fill the gap where there aren't enough experts and allow for quicker treatment.

In our research we have employed the deep learning techniques to detect and classify Tuberculosis and Pneumonia. Initially in first stage we trained autoencoders to detect the anomaly in the chest X-ray images. In second stage we used the deep learning models InceptionV3 and Xception along with Grad-Cam to classify and spot the disease with a heatmap on the chest-Xray image.

2. Related work

In this section we presented a brief discussion and review of recent work on detecting and classifying Tuberculosis and Pneumonia using deep learning models. In [1] the authors proposed an novel CNN model called CDC_net for classifying multiple chest infections. They introduced residual network block and dilated convolution block to calculate difference between expected and actual values while maintaining the feature map resolution. This proposed model has outperformed the other transfer learning models i.e., Vgg-19, ResNet-50 and Inception-V3. In [2] the authors addressed the challenges class imbalance and overfitting with data augmentation and SOMTE techniques. They proposed a Deep Neural Network for multi-level classification of lung diseases from chest Xray images. Their model shown outstanding results after class balancing after using SMOTE techniques compared to without SMOTE techniques.

In [3] the authors introduced a CNN architecture that can detect whether Xray is normal or abnormal with Pneumonia or Tuberculosis. In [4] the author proposed a novel CNN architecture integrated with XAI methods Grad-Cam, LIME, SHAP for explanation of classification. Their work has shown outstanding results in classifying the Diseases from chest Xray Images. In [5] the authors developed a custom model ConvNets. They tested the model performance on both balanced and unbalanced data and found that model with unbalanced data has shown bias for the major class. They deployed the model using Streamlit.

In [6] the authors introduced a neural network architecture for classification of multiple lung disease. They applied data augmentation techniques to address the class imbalance. The neural network is fed with images to train and classify. Their proposed framework efficiently classified the different pulmonary infections. In [7] the authors proposed a novel deep transfer learning pipeline DenResCov-19 to classify multiple lung disease from Xray images. They concatenated the DenseNet-121 with ResNet-50 and extra CNN block. The proposed model outperformed the individual models Dense-

Net-121 and Resnet-50 in classifying TB, Pneumonia and Covid-19.

In [8] the authors used transfer learning models ResNet-50, Xception, DenseNet-169 for classifying the Xray images into Covid-19, pneumonia and TB. Initially they used cGAN to generate new images to address the challenge overfitting and trained the transfer learning models. The ResNet-50 outperformed other transfer learning models in classifying diseases.

In [9] the authors proposed a convolution architecture that takes the grayscale images as input. The model has shown significant results in classifying the disease from Xray images but shown low accuracy in classifying the Covid-19 when the model is trained on imbalanced data where Covid-19 is minor class.

In [10] the authors proposed a deep learning model which is trained on the dataset comprising of true labels for pneumonia, TB and Covid-19. The performance of the proposed model is compared with the traditional machine learning techniques SVM, decision trees and XGBoost. In [11] the authors extracted the LBP and HOG features from the CXR image dataset. These features are fed to different classifiers Random Forest, Support Vector Machine, Extreme Gradient Boosting and Logistic Regression and Ensemble model for classification of COVID-19, TB and Pneumonia. The proposed ensembled model has achieved an highest accuracy in outperforming the other models.

In [12] the authors implemented the deep learning models , VGG16, ResNet50, MobileNet, DenseNet and InceptionV3 to classify Tuberculosis and Pneumonia from Xray images. Their work has shown that InceptionV3 achieved highest accuracy in classifying the disease compared to other models. In [13] the authors implemented two stage proposed system i which stage 1 is used to classify three classes of lung disease. Further in second stage the ensembled model is used for classifying the Pneumonia into Regular Pneumonia or Covid Pneumonia. In Stage 1 Inception V3 outperformed other deep learning models and in stage 2 the ensembled model of EfficientNetB0, Xception and DenseNet201 outperformed other combination of models.In [14] the authors implemented a variational autoencoder to anomaly detection in Chest X-ray images. The model was trained on extensive amount of normal Xray images and tested on anomaly images and normal images. The model has demonstrated promising results in detecting anomaly in the Chest X-ray images. In [15] proposed a novel hierarchical structure comprised of new networks CXnet-m1, CXnet-m2, CXnet-m3, CXnet-m4. These are binary classifiers used in different stages of architecture to classify the images based on the labels of the data. In stage 1 CXnet-m1 is used to classify among the normal and abnormal images. In stage 2 CXnet-m2 is used to classify multi label and single label images. In stage 3 CXnet-m3 and CXnet-m4 are used to classify the disease.

Dataset

In our work we created a custom dataset of Chest X-ray images of Tuberculosis, Pneumonia from the Kaggle datasets **“Chest-xray-pneumoniacovid19tuberculosis”** and **“tuberculosis-tb-chest-xray-dataset”.** Our data set consist of three classes **“Normal”**, **“Pneumonia”** and **“Tuberculosis”.** Each class consist of 1500 images.

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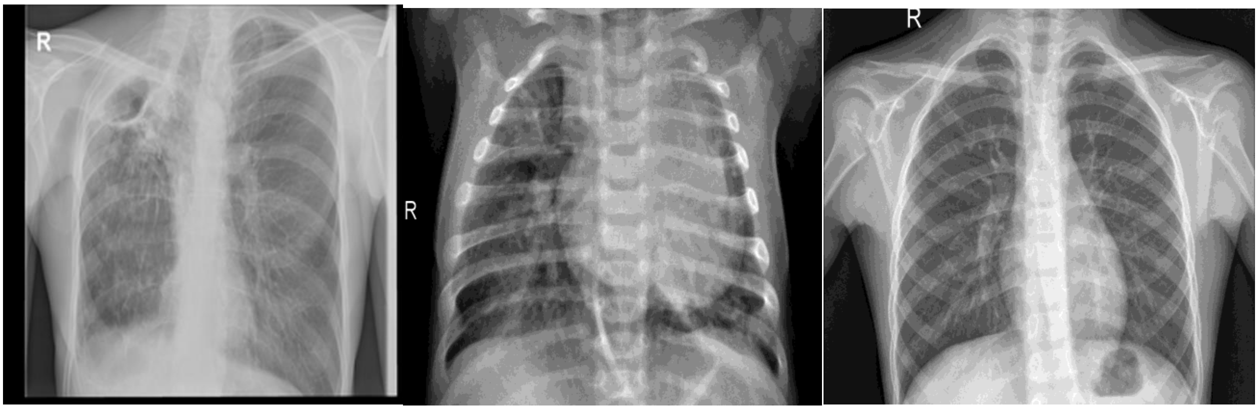


Tuberculosis **Pneumonia** **Normal**

3. Methodology

Our study comprised of two stages – Anomaly detection and Classification. Initially we collected normal, Tuberculosis and Pneumonia Chest X-ray images from publicly available Kaggle dataset Chest X-Ray (Pneumonia, Covid-19, Tuberculosis). After collecting the data, in data processing phase the images are resized to 224x224 pixels.

In Stage 1:

The resized normal chest X-ray images are fed to the auto encoder for anomaly detection. In this stage we have applied one class-learning. The model was trained on only "normal" chest X-ray images. It detects the image as anomalous if there is any deviation between the original and reconstructed image. The anomalous images indicate diseases like Pneumonia or Tuberculosis which have deviation from normal patterns.

The model constitutes of Encoder and Decoder. The Encoder compresses the input image into a lower dimensional representation known as latent space. This compressed feature map with reduced spatial dimensions are passed to decoder. The decoder reconstructs the image from the compressed latent representation. Once the image is reconstructed the reconstruction error is calculated using Mean Square Error. If the reconstruction error is more than the threshold value the image is detected as anomalous else it is detected as normal.

In Stage 2:

When the image id detected as anomalous it is directed to stage 2 to classify and detect the disease in the Chest X-ray image. In this phase we employed two deep learning models InceptionV3 and Xception for classifying Tuberculosis and Pneumonia from chest X-ray images. The resized images of Tuberculosis and Pneumonia are fed to both the models. Xception is an extension of the Inception V3 architecture. Inception V3 uses the "Inception module" with the multiple filters of different sizes whereas Xception is mainly focused on the depth wise separable convolutions which makes it achieve high accuracy with less no of parameters. Therefore, Xception generalizes the idea behind the Inception V3 by making convolution operations more efficient and improving model's performance on large-scale image classification tasks. We employed the pre-trained ImageNet weights on both the models. These weights of ImageNet provide the model with strong understanding of basic image features of edges, texture and shape.

We used Grad-CAM (Gradient-weighted Class Activation Mapping) to explain the decision making of the model. It generates the heatmap visualization using the gradients from the final convolution layer of the model. In case of InceptionV3 the final convolution layer is "mixed10" and for Xception it is "block14_sepconv2_act". The heatmap generated by the Grad-CAM has shown which part of the lungs are affected by the disease classified by the model.

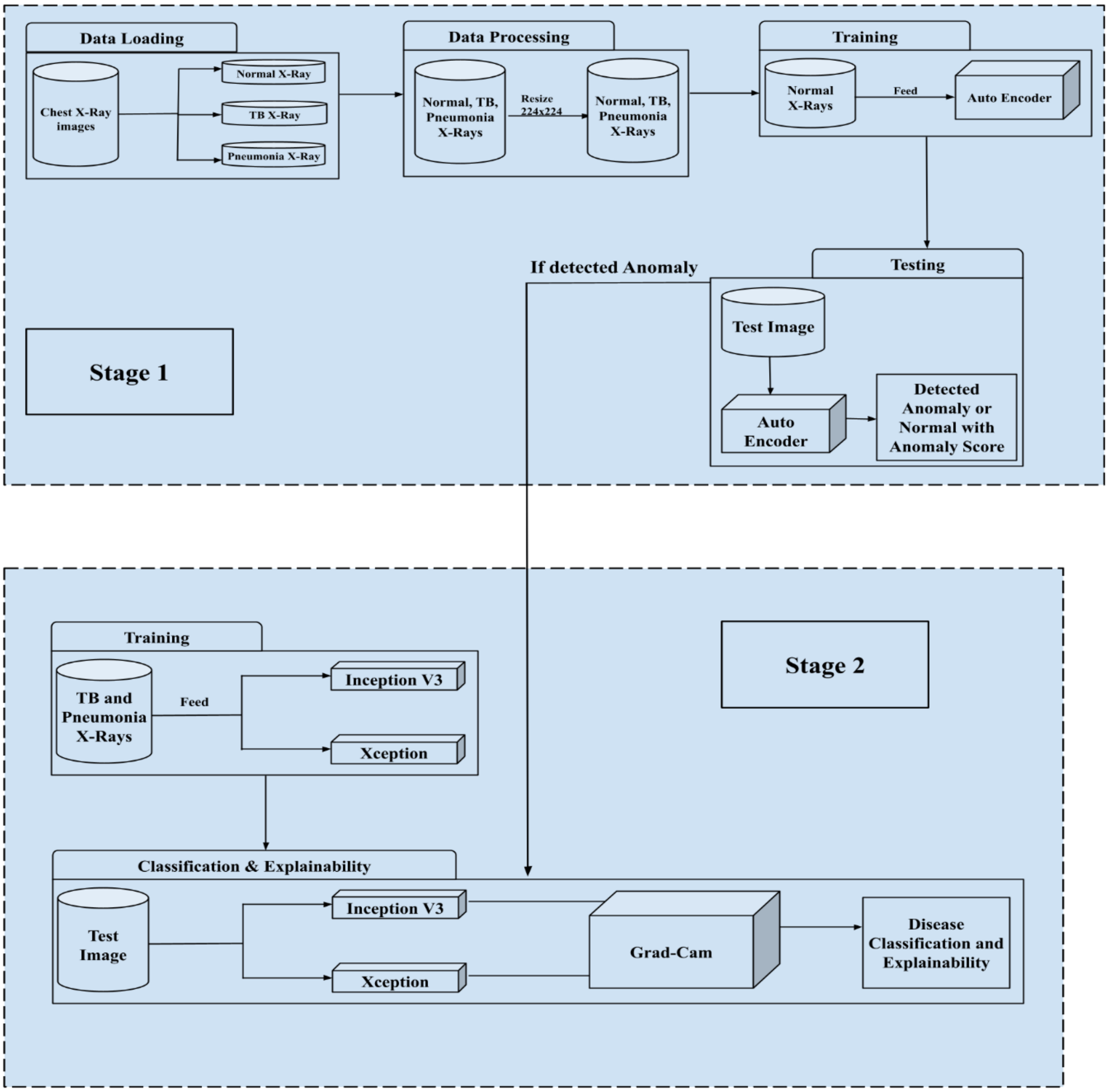
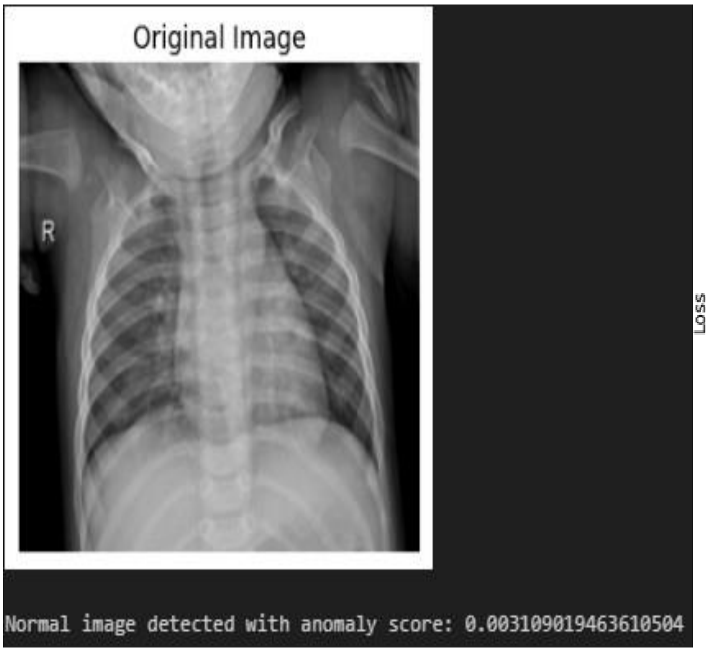


Fig1:Architecture Diagram

Results Stage1:

In stage 1 we trained autoencoder on only normal images for anomaly detection which has shown promising results in detecting the anomaly.Fig2 shows the detection of normal image by autoencoder. Fig3 shows the ROC curves of loss metrics of autoencoders.



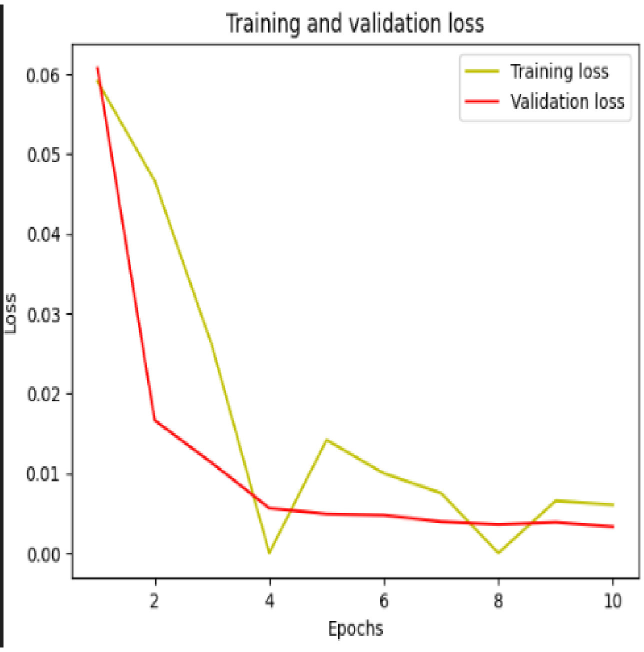


Fig 2 : normal image detection with anomalous score autoencoder

Fig 3: ROC curves of loss metrics of

Stage 2:

In stage 2 we trained the deep learning models Xception and Inception V3 with the Tuberculosis and Pneumonia chest X-ray images. Xception achieved an accuracy of 100% and Inception V3 achieved an accuracy of 99.77% in classifying the disease.The red spot in the Grad-CAM image indicate the disease spot. Fig 4,5,6,7 represent the results of Xception model.

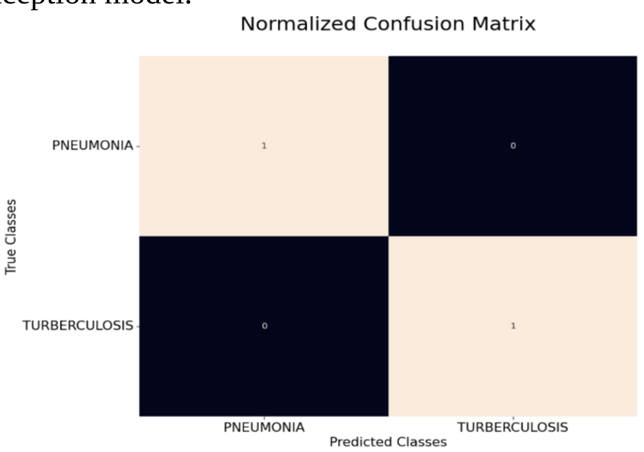


Fig 4: Grad-CAM visualization

Fig 5: Normalized Confusion matrix

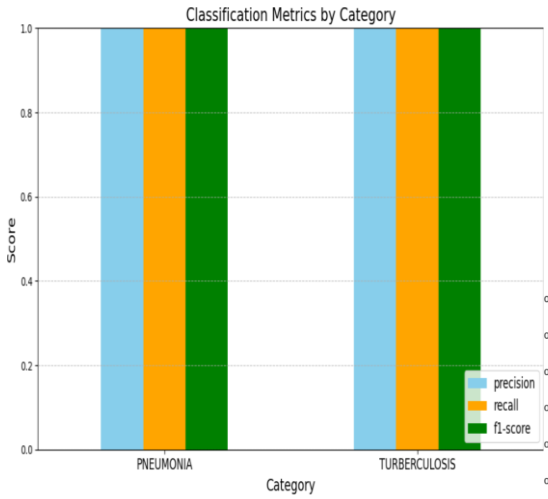


Fig 6: Classification Report

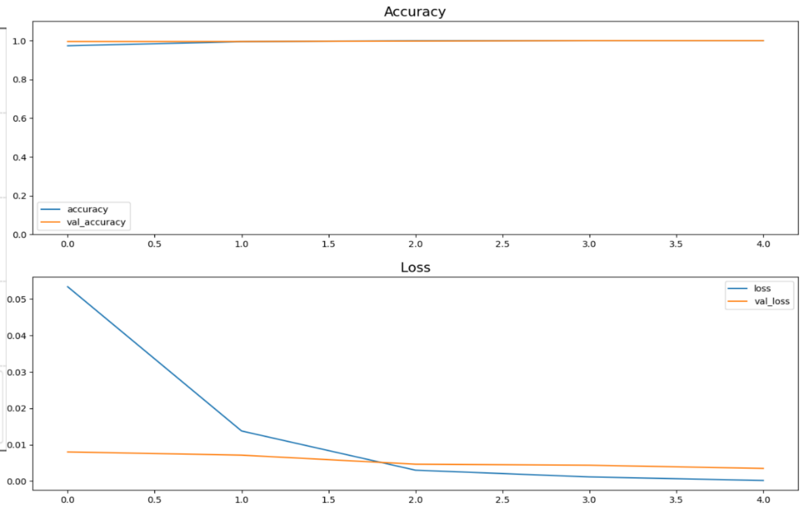


Fig 7: ROC curves of Training and Validation

Fig 8,9,10,11 represent the results of Inception V3 model.

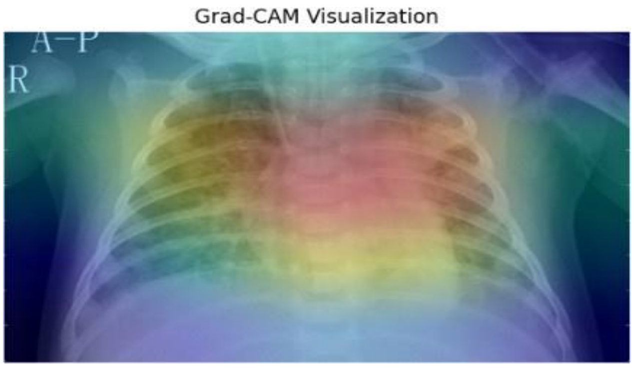


Fig 8: Grad-CAM visualization

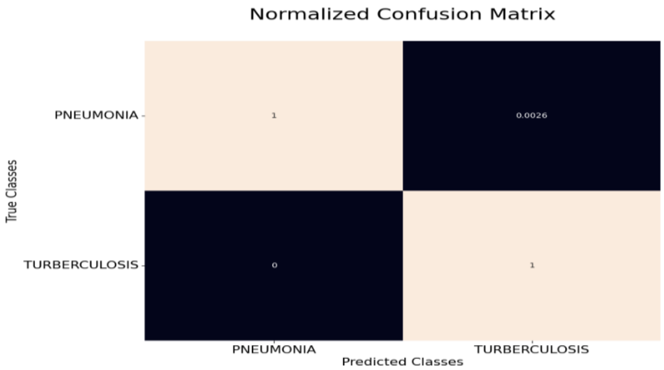


Fig 9: Normalized Confusion Matrix

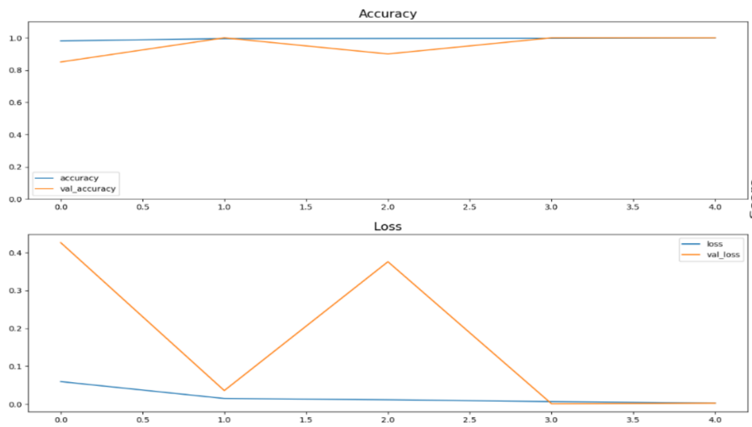


Fig 10: Classification Report

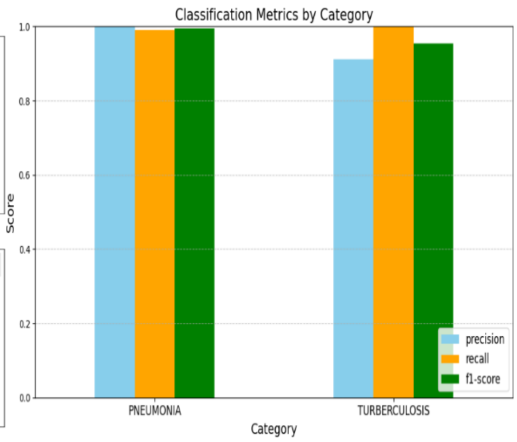
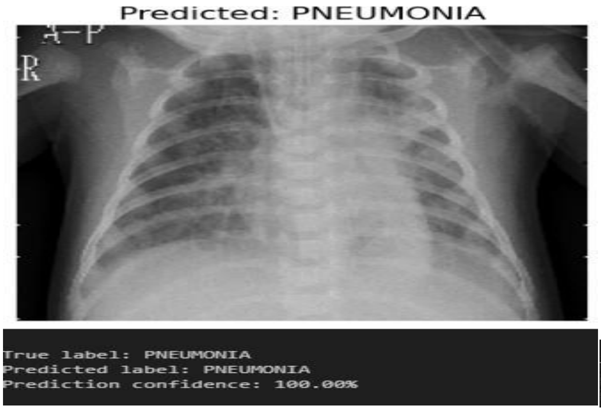


Fig 11: ROC curve of Training and Validation

Fig 12 & 13 represent the predictions of Xception and Inception V3 model



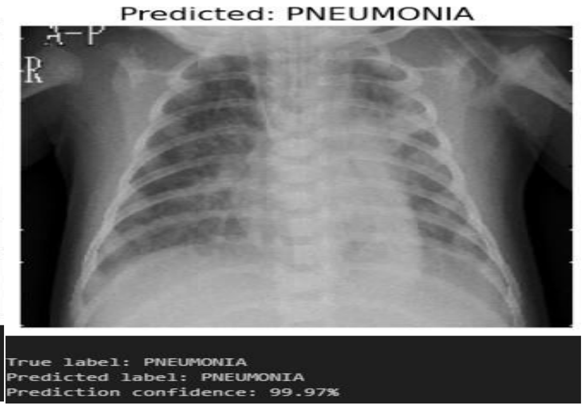


Fig 12 : Xception Prediction

Fig 13 : Inception V3 Prediction

4. Conclusion and Future Scope

In our study we employed two stages. In stage one we trained an Autoencoder model with only one class i.e., normal chest X-ray images. Thus, making the model efficient in detecting the anomalous patterns in the test image compared to normal pattern in normal chest X-ray image. When the model detects anomaly, it is directed to stage two where the deep learning models are trained o classify the chest diseases. Xception has outperformed InceptionV3 in classifying the lung diseases i.e., Tuberculosis and Pneumonia. Grad-CAM made it easier to trust the models result in classifying the disease because of generated heatmap pointing out the disease spot in image. Using Explainable AI techniques with deep learning models make it easier for detecting disease spot.

Our research has limitation with model trained on only two diseases. In future we would train the deep learning model with more no of chest diseases images making the model more efficient in classifying those diseases accurately.

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