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Automated Segmentation of Pneumothorax Using Deep Learning

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***Abstract:** Pneumothorax, which refers to the presence of air within the pleural cavity and may cause fatal consequences for a patient, necessitates timely and precise diagnosis. Existing approaches to pneumothorax detection based on analysis of chest X-rays manually tend to be both time-consuming and error-prone. In this regard, the current project seeks to develop an automated approach that will allow detecting and segmenting pneumothorax accurately via deep learning models. With the use of convolutional neural networks (CNNs), especially the ones that rely on U-Net architecture, the model learns to detect and segment the areas affected by the condition from chest X-rays. Such an algorithm is intended to help radiologists with diagnostics and improve their workflow efficiency. Specifically, the proposed solution includes a web application that can take chest X-rays from users, analyze them, and show segmented areas on X-rays instantly. In this way, AI-based pneumothorax detection and segmentation will enable more rapid and precise clinical decisions regarding the disease treatment. The model has been developed with the help of PyTorch, using a U-Net architecture and EfficientNet-B3 encoder, having achieved approximately 0.47 Dice score for validation.*

I. INTRODUCTION

The fast pace of development of artificial intelligence (AI) and deep learning (DL) has led to a paradigm shift in medical diagnostics. These technologies have been used to solve some of the longstanding issues in medicine. In today's world, the number of patients has increased dramatically, while the number of radiologists remains low. As a result, automatic methods of diagnostic analysis are becoming more relevant. Medical imaging plays a key role in disease diagnosis since it provides doctors with crucial information to make their decisions about treatment plans. Nevertheless, the amount of information produced by imaging is growing rapidly, which makes it difficult for humans to analyze. Thereby, there is a need for artificial intelligence-based models that could help diagnose diseases faster and more accurately.

One of the most important diseases that require immediate detection is pneumothorax, also known as collapsed lung. Pneumothorax is an acute condition that results from air accumulation between the chest and lungs. This disease might lead to severe complications, including respiratory insufficiency, shock, and even death. Traditional chest X-ray scans are used to diagnose pneumothorax. However, the nature of such diseases may make it difficult for radiologists to interpret the radiographic images correctly and timely due to their subtle presentation and variable quality of images. Failure to do so in critical situations may lead to disastrous outcomes. Hence, the introduction of automatic, reliable, and rapid diagnostic tools is currently a pressing need.

Deep Learning is one of the most promising ways to analyze the medical images with high accuracy and consistency. One of the most popular neural networks used for such tasks is Convolutional Neural Network. In the scope of different architectures proposed, the most famous is the U-Net – neural network used in biomedical image segmentation. It uses the idea of encoder-decoder, which allows for classifying all the pixels of the image. As a result, using this network allows highlighting certain parts of the picture, making it ideal for detecting and segmenting the areas of interest. Therefore, it will be possible to detect the regions of interest associated with a pneumothorax in chest X-rays with high accuracy. The main aim of this project is to implement deep learning algorithms to create an effective automated system that can identify pneumothorax regions in chest X-rays.

On the other hand, the peculiarities of such types of diseases can become a hindrance for interpreting the images by radiologists because of their inconspicuousness and poor image quality. Such failures in interpreting the images in a timely manner in critical situations might result in a catastrophic outcome. Thus, the development of automatic and accurate diagnostic instruments becomes a topical issue at the moment.

Among other methods that can help with analyzing medical images effectively, Deep Learning stands out as one of the most promising approaches. The most commonly used neural networks in this field include Convolutional Neural Networks.

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Among different architectural designs, the most renowned network in this field is U-Net. U-Net is the neural network that utilizes the approach of encoder-decoder and allows for classifying all the pixels in the image.

As a consequence, this network helps highlight some areas on the image and makes it ideal for segmenting the particular area. Thus, U-Net can be used for detecting and separating areas where there is a pneumothorax in chest X-rays.The aim of the project is to apply Deep Learning algorithms for the creation of an automated identification system for detecting pneumothorax regions in chest X-rays.

II. MOTIVATION

The growing need for fast and precise diagnosis in the medical field, along with the lack of qualified radiologists, has led to an essential requirement for automated intelligence systems in the health care sector. Pneumothorax is a deadly condition that needs prompt detection and treatment; however, it is often difficult to detect pneumothorax in chest x-ray images due to its complex visual features. Any delay or misinterpretation during the process could cause harm to patients. Recent innovations in Artificial Intelligence and deep learning techniques have shown great potential in image processing in medicine. Segmentation algorithms, such as U-Net, have proven effective in detecting anomalies in radiographic images on a pixel-by-pixel basis. Motivated by these advances, this paper proposes a deep learning-based model to detect and segment pneumothorax in chest x-rays. The model training can be used in order to integrate a diagnostic tool into a convenient web-based interface which will provide real-time diagnostics assistance to health professionals.It will assist radiologists in their work as it can decrease their workload, ensure diagnosis consistency and help them make their decisions faster, particularly in emergency cases or hospitals where medical personnel have a minimum medical background.

III. WORKING PRINCIPLE

The working principle of the proposed system for pneumothorax detection and segmentation is built on deep learning-based image processing. In this case, the first step involves providing a chest X-ray image as the input data to the system. Afterward, several processes are applied to the image, including image sizing, normalization, and denoising, which allow preparing the image for the further stages of processing. Once all the preprocessing steps have been applied to the initial input image, it is fed to the U-Net trained model consisting of an encoder-decoder. The trained model employs patterns that have been learned from the training dataset to segment healthy parts of lungs from parts that have pneumothorax. After segmentation is performed, the mask is overlaid on top of the image to facilitate visualization of the affected part. The model predicts probabilities for the occurrence of a specific object within an input image using a sigmoid function, which results in a binary mask after thresholding(≈ 0.5). In addition, the algorithm can also calculate a confidence level that indicates how reliable the prediction made by the model is finally, the output image is delivered to the user via a web interface to facilitate real-time analysis.This approach makes it possible to enable medical professionals to detect pneumothorax.

IV. LITERATURE SURVEY

K.R.Sowmia et al. (2024) proposed a deep learning-based hybrid architecture which uses DenseNet-121 to classify pneumothorax images and UNet++ for segmentation of the same. The architecture helps to localize and interpret the results effectively. The drawback of the architecture is that it is trained on data from only one center and cannot generalize to other centers.[1]

According to J.Manikandan et al. An end-to-end approach has been developed that uses the CNN classifier with the U-Net segmentation model for automatic detection of pneumothorax. The algorithm is able to classify and localize the condition simultaneously, making it more efficient than conventional machine learning algorithms. Nevertheless, there is a lack of balanced training data in the algorithm.[2]

Asghari et al., 2025 Proposed a bespoke CNN architecture for binary classification through the use of the NIH chest x-rays data set. It is evident from their experiment that deep learning approaches are more effective than classical methods such as SVM, Random Forest, and decision tree. However, even though the performance was relatively high, it failed on certain issues.[3]

Lee et al. (2024) S. Conducted a comprehensive real-world performance analysis of an off-the-shelf artificial intelligence system based on more than 87,000 chest X-rays. The authors emphasize that even highly accurate algorithms can generate false positives owing to such imaging artifacts as skin folds, medical equipment, and anatomical overlap. They recommend threshold adjustment in the clinical setting beyond accuracy measures.[4]

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Sae-Lim et al. (2024) W.Developed a novel two-step deep learning algorithm, which involves initial lung segmentation via U-Net and subsequent pneumothorax localization through PTXSeg-Net with attention capabilities. The network demonstrates remarkable segmentation performance (Dice ≈ 0.91) and pneumothorax quantification. However, it was not validated with CT scans, nor does it address disease progression.[5]

Dumbrique et al., J. I. S. (2024). Proposed the use of a patch-based Fully Convolutional Neural Network (FCNN) that enhances segmentation accuracy, particularly in detecting thin pleural lines. This model, although efficient, needs thorough validation through multi-centered data. [6]

Ibañez Caturla, S. (2025). Emphasized improvement in cross-domain generalization using multi-source data and domain adaptation in an Efficient Net based model to minimize overfitting issues. The model, despite its efficiency, lacks validation in the practical world. [7]

Comparison between AI based pneumothorax detection and radiologists' detection performances in clinical practice; C. B. Monti et al. (2025) In this study, it was revealed that while AI-based detection showed similar sensitivity, it produced more false positives, which could negatively impact the confidence of clinical use.[8]

Lung Ultrasound Images-Based Detection of Pneumothorax Using Deep Neural Networks; S. Montgomery et al. (2023) This study aimed to investigate the applicability of AI in pneumothorax detection through lung ultrasounds; although the results were positive, the small sample size consisting of only 30 patients limited the applicability of the model.[9]

V. SYSTEM ARCHITECTURE

Architecture for automated pneumothorax segmentation will be implemented in the form of a pipelined approach, which combines deep learning algorithms and software.

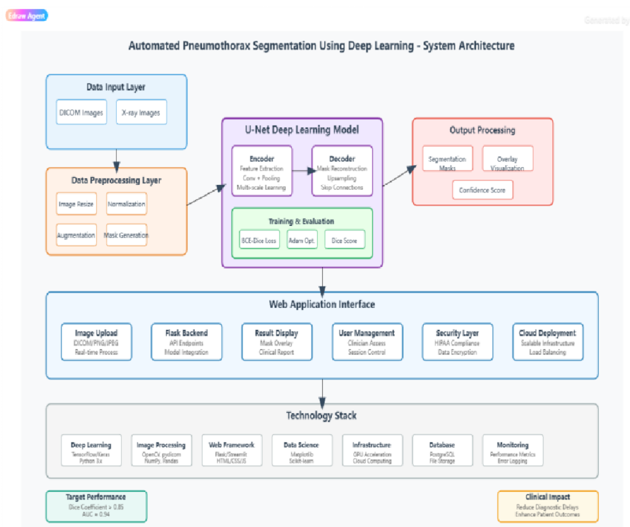

Fig 1:-System Architecture

The first layer is related to the data input layer when chest X-rays images in formats, for instance, DICOM and PNG FORMAT (CONVERTED FROM DICOM) are given as input into the system. Next, pre-processing is carried out for image resizing, normalization, augmentation, and masking. Then, the pre-processed image will undergo U-Net deep learning model, in which a convolution/pooling encoder layer will be responsible for feature extraction, while the decoding layer will restore the image by upsampling and skip connections to provide precise segmentation at the pixel level.

During training, optimization approaches will be utilized to minimize losses in the learning process. As far as the loss function and optimization approach are concerned, Focal Tversky Loss can be applied along with Binary Cross-Entropy (BCE) for optimizing the process via AdamW.

Post-processing takes place on the output of the model to create segmentation masks that are placed over the original X-ray images, alongside confidence scores. The processed results are then made available via an online application interface. The interface comprises various elements like modules for uploading the images, processing of the data at the back end, visualization of results, user management systems, and other features including data security and encryption.

The entire system operates using a solid technology stack. The tech stack incorporates tools such as PyTorch with segmentationmodelsPyTorch (SMP) for deep learning, OpenCV for image processing, and Streamlit for developing a web app interface. The infrastructure involved is also important because it uses cloud or GPU resources.

VI. METHODOLOGY

In the proposed system, an automated deep learning approach is adopted to detect and segment pneumothorax from chest X-rays using the U-Net architecture. This process is performed in accordance with an end-to-end methodology involving data acquisition, preprocessing, model development, training, validation, inference, and deployment stages.

1) Data Acquisition

The data acquired for use in this paper includes DICOM chest X-ray images, together with corresponding Run-Length Encoded (RLE) masks, taken from the publicly available SIIM-ACR Pneumothorax Segmentation Dataset. This set contains 2,379 image-mask pairs altogether, of which 1,903 will be used for training and the remaining 476 images for validation purposes. Examination of the data shows that the pneumothorax areas take up only a small part of each image, roughly between 1% and 2%.

2) Data Preprocessing

The DICOM images were initially transformed to common image formats like PNG or JPEG. The dimensions of each image were uniformly set at 384×384 pixels, striking a balance between efficiency and adequate resolution for precise segmentation. Images in grayscale format were then converted to three-channel images to make them compatible with the pretrained encoder models. They were standardized to have a mean value of 0.5 and a standard deviation of 0.5. The RLE masks were decoded to create binary segmentation masks for the pneumothorax areas. To enhance generalization and mitigate overfitting, various data augmentation strategies were employed, which included horizontal flips,
rotations, zooming/scale changes, and slight changes in brightness/contrast. Following data augmentation, the masks underwent re-binarization to avoid introducing soft values.

3) Model Development

The segmentation model follows a U-Net architecture that has been developed specifically for the task of pneumothorax segmentation. In this context, the encoder acts as the contraction layer to extract feature information from the input images, whereas the decoder serves as an expansion layer to restore the spatial dimensions in order to localize the relevant regions of interest. Through skip connections between the matching layers of the encoder and decoder, the model can learn both low-level and high-level features, thereby improving its ability to perform segmentation tasks for smaller and subtle pneumothorax regions. The encoder architecture uses EfficientNet-B3.

4) Model Training

In order to have an appropriate evaluation and generalization of the model, the dataset was partitioned into three parts: training, validation, and testing datasets. In order to address class imbalance caused by the small region of pneumothorax, BCE and Dice losses were utilized to train the model. The AdamW optimizer was used to facilitate learning. Mixed precision computation and monitoring in the validation set were also included in the training procedure to avoid overfitting and obtain fast computation, respectively. Moreover, the optimal segmentation threshold value was determined through multi-threshold evaluation in training.

5) Model Evaluation

Model evaluation was done using a number of metrics such as Dice Coefficient, Intersection over Union (IoU), Precision, Recall, and Accuracy to give a detailed overview of the model’s segmentation abilities. Besides these metrics used in evaluating the model quantitatively, there is also the use of a qualitative approach that entails applying visual overlay of the predictions on the real chest X-rays images to clearly see how well the model segments the regions of pneumothorax.

6) Inference and Visualization

In the process of making an inference, the trained model produces binary masks for unseen images from chest X-rays indicating the areas with pneumothorax. The binary masks are overlayed on top of the images to help clinicians quickly and accurately interpret the images.

7) Web Application Deployment

The model is integrated into a web application framework like Streamlit, Flask, and Gradio and enables the uploading of new images. Preprocessing in the application uses the same techniques as preprocessing done while training the model to make accurate predictions. The application offers real-time inference and visualizes the predicted mask overlaid on top of the image to help clinicians interpret the images quickly. This deployment method makes the application easily accessible in any clinical environment, even in emergency situations and remote locations, where the model weights can be stored on Google Drive or GitHub.

8) Further Improvements

Further improvements for the network include enhancing its ability to handle high resolution input images such as 512×512 to better detect small features. A combination of strong encoder models or transformer-based segmentation models might help in this regard. In addition, Test-Time Augmentation might be used to improve the reliability of prediction, while the issue of imbalance in the dataset or few foreground pneumothorax areas might be dealt with using augmentation techniques. Altogether, these advancements are aimed at boosting the effectiveness of the model, especially to achieve Dice score over 0.65-0.70.

VII. DATASET

The datasets employed in this proposed pneumothorax detection system establish an organized and systematic environment for images. The main dataset that will be employed in this system is the SIIM-ACR Pneumothorax Segmentation dataset (Kaggle), comprising chest X-ray images and segmentation masks annotated by experts. This is the main dataset from which the fully-supervised deep learning model will be trained. In terms of features, the chest X-ray images have DICOM ID, file path, modality of imaging (AP/PA), resolution, anonymized patient IDs, and DICOM metadata such as pixel spacing, view position among others.

Apart from the images, the dataset contains pneumothorax segmentation masks that act as ground truth for model training. The segmentation masks are encoded using RLE and represent the exact pixels where the lung has collapsed. Key features in the masks include mask ID, encoded pixels, mask area, and laterality among others. Such information is important in training segmentation algorithms such as U-Net and other variants. Additionally, DICOM tags contain valuable patient information including study ID, series ID, image orientation (AP/PA), pixel spacing, and optional age and gender of the patients. This type of information can be very useful in preparing data for use in the medical image analysis process.

Moreover, the dataset contains additional labels that classify the presence or absence of pneumothorax. Other additional features can be included such as severity levels of pneumothorax, number of locations, and source(s) of annotations (i.e., experts). As the model trains on data, interaction logs will be created. Some of the information contained in the logs is input image tensors, output predictions, loss values, extracted feature maps, and training decisions. This information plays an important role in improving model performance by helping to optimize learning rate, perform early stopping, and others.

Lastly, the dataset will contain hard cases of chest radiograph images. Examples include under-exposure, over-exposure, motion blur, subtle regions of pneumothorax, and anatomical structures superposition among others. Such hard cases provide a challenge to the model since they represent difficult conditions that are encountered in real world clinical environments.

An integrated set of modern technologies is utilized to implement the proposed detection and segmentation model. This includes technologies related to data preprocessing, building models, evaluating them, and deploying them. Python is utilized as the primary programming language for building AI models for the proposed system. Being a simple yet effective programming language for AI and machine learning tasks, Python can be easily utilized for implementing the complex model.

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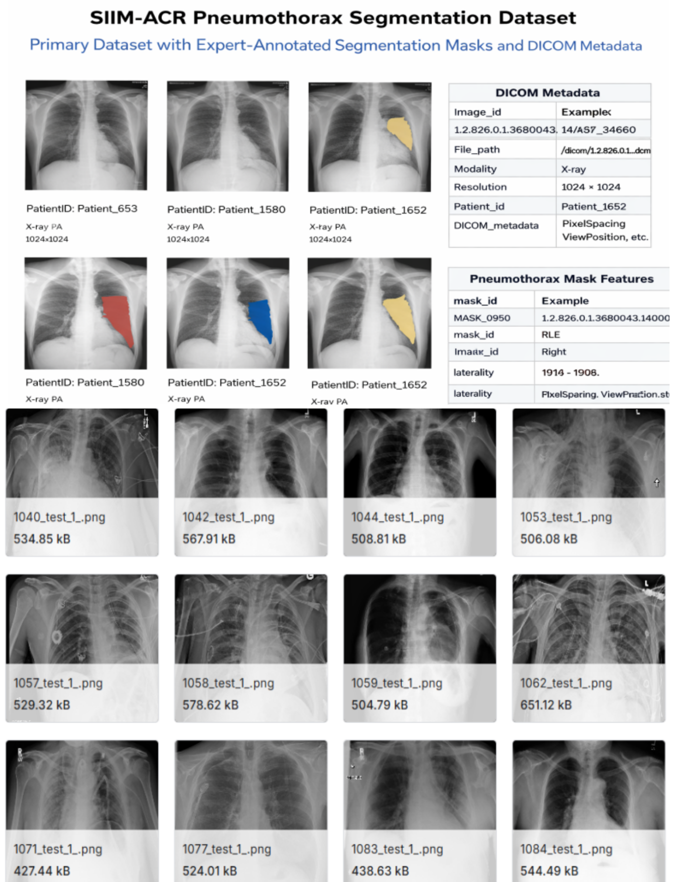


Fig 2:-Dataset Images

As part of development and experimentation, the project is implemented in Kaggle notebook with support for GPU-based calculations. This is done because the notebook environment provides good performance in terms of deep learning training. Apart from Kaggle notebook, Jupyter notebook and Visual Studio Code are also utilized.

VIII. TECHNOLOGY USED

The deep learning architecture is realized in PyTorch in conjunction with the Segmentation Models PyTorch (SMP). Using this approach allows implementing sophisticated models such as U-Net with the EfficientNet encoder (EfficientNet-B3), utilized for segmentation of medical images within this particular task.Image augmentation and preprocessing are done using the powerful Albumentations package. It provides fast and flexible functions, which allow rescaling images to a particular size (512x512), normalization, horizontal flip, adjusting thebrightness and contrast of the image, adding noise.

Considering that the dataset contains X-rays of the chest and corresponding binary masks, typical pre-processing steps for images were carried out, namely converting grayscale images into images with three color channels and binarizing the mask images. Computations and mathematical operations with tensors are made possible with the aid of the numpylibrary.Data loading and batching are performed by the PyTorchDataLoader.

For model optimization purposes, the AdamW optimization algorithm and the reduceLROnPlateau scheduler will be used. The proposed method uses a hybrid loss function that combines Focal Tversky loss and binary cross-entropy (BCE), which allows addressing the problem of unbalanced classes and increases the accuracy of segmenting small parts of pneumothorax.

Model evaluation will be performed based on such metrics as the Dice coefficient (main metric) and Intersection over Union (IoU). Such metrics play a significant role in determining the effectiveness of segmentation, especially in cases when the target area in medical images is much smaller than the background.

In order to increase training speed and reduce GPU memory consumption, AMP is used. For visualization and analysis purposes, Matplotlib is Streamlit, on the other hand, is the deployment tool that is used to deploy the software, and the same is a lightweight framework that helps build a fully interactive UI for the deployment process.

The deployment system provides the user with the ability to upload chest X-ray images, preprocess images, generate model inference output, and visualize segmentation predictions.Trained model weights are stored in a different location outside of the system by making use of Google drive and can be accessed easily by dynamically loading models into applications through utilities such as gdown. Git/GitHub are used to maintain version control of the codebase.

As a whole, the above technologies have been used effectively to deploy an end-to-end system that can effectively detect pneumothorax from the chest x-rays. During the inference time, the models give out logit outputs which are further converted to probabilities using sigmoid activation functions.

IX. RESULTS

USER INTERFACE PAGE

The model was able to get a validation dice score of around 0.47. Because of the small size of the pneumothorax areas, there is a difficulty in getting better dice scores due to class imbalance. But still, the model can identify which areas are affected and provides valuable segmentations.

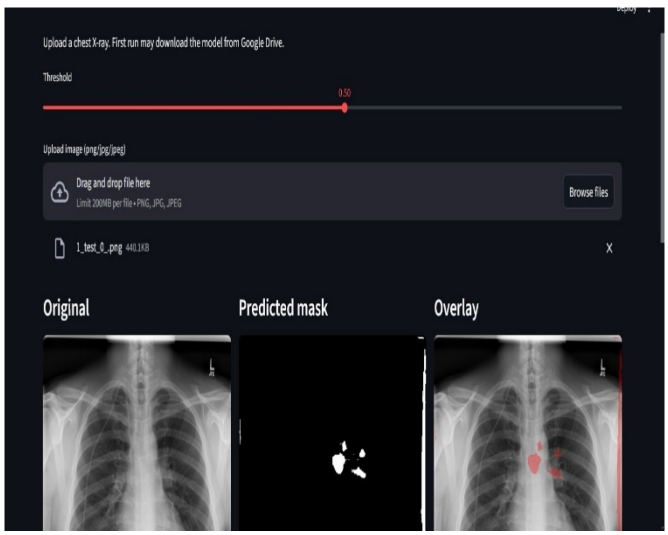
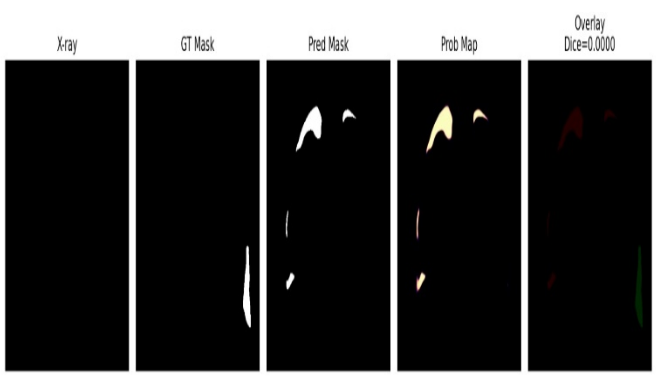


Fig 3:-Home Page



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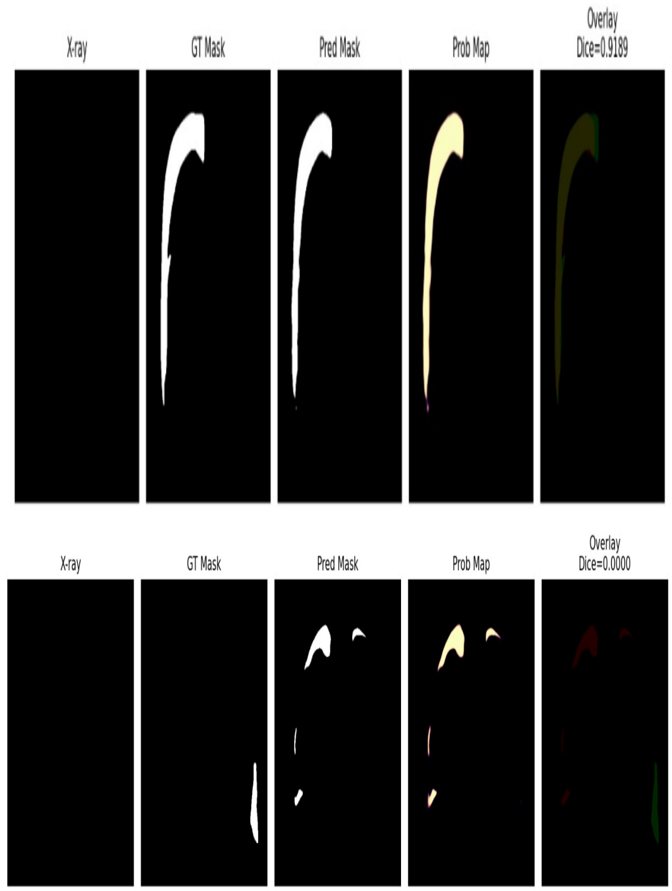

Fig 4:-Outputs

X. CONCLUSION

This project sought to develop an automated system that could detect and segment pneumothorax from chest X-ray images through the use of deep learning. This goal was accomplished as an end-to-end system that included preprocessing, data augmentation, model training, evaluation, and visualization of results. A model architecture based on U-Net segmentation and the EfficientNet-B3 encoder was constructed using the Python framework, PyTorch. The model was trained on chest X-rays labeled for the presence of pneumothorax, with class balancing performed through the use of a hybrid loss function. The model showed the capability of learning features and accurately segmenting pneumothorax areas in the images.

XI. FUTURE SCOPE

Though the existing system provides excellent performance in segmenting pneumothorax from CT scans, there are some areas where the system can be improved upon. Firstly, the model's performance can be enhanced by using more comprehensive data sets which have both positive and negative cases. Secondly, increasing the resolution of the images being segmented from the current level of 384 × 384 will provide better results, since this will allow for better segmentation of small areas where the problem may lie. Architectures like U-Net++, Attention U-Net, and even transformer-based models can be experimented with as well. Loss function experiments, TTA, and optimizing the threshold value are other steps which can be taken to improve results obtained by the model. Better handling of class imbalances at both pixel and data set levels should be considered for increased performance and accuracy. Finally, the current Streamlit prototype can be deployed as an application accessible via web or the cloud. The solution thus generated can then be integrated with hospitals' PACS to provide a practical solution for radiologists. Moreover, the system may be extended for multi-class segmentation that would enable it to detect additional lung diseases like pneumonia, tuberculosis, or even lung nodules. Lastly, clinical testing by healthcare professionals is crucial in assessing the practical application of the proposed algorithm. Input from the radiologists may further improve the algorithm's reliability and facilitate its safe implementation.

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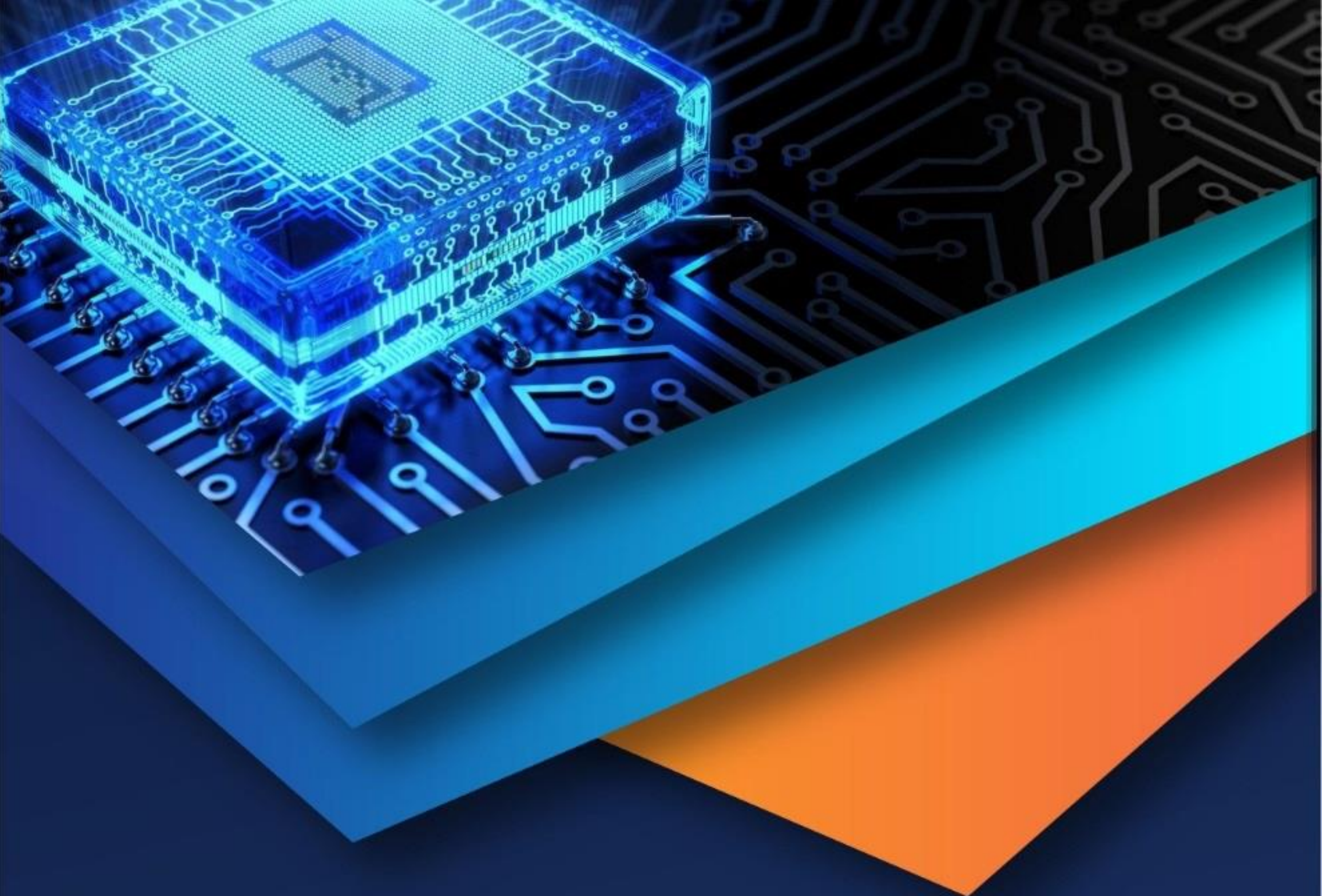

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