

LOOP RESIDUAL ATTENTION NETWORK FOR AUTOMATIC SEGMENTATION OF COVID-19 CHEST X-RAY IMAGES

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Abstract—The rapid global spread of the COVID-19 pandemic has highlighted the importance of efficient and automated diagnostic systems that can assist healthcare professionals in detecting and analyzing lung infections. Chest X-ray imaging is widely used for COVID-19 screening because it is readily available, cost-effective, and capable of providing quick imaging results. However, manual interpretation of chest X-ray images by radiologists can be time-consuming and may lead to diagnostic errors, especially when large volumes of cases must be evaluated during pandemic situations. To address these challenges, deep learning techniques have been increasingly applied in medical image analysis due to their ability to automatically extract meaningful features and identify disease patterns from complex imaging data. In particular, attention-based neural networks have shown promising performance in highlighting important infection regions within medical images.

This study proposes a Loop Residual Attention Network for the automatic segmentation of COVID-19 infection regions in chest X-ray images. The proposed model combines residual learning with attention mechanisms to enhance feature extraction and segmentation accuracy. Residual connections enable the network to learn deeper representations while mitigating the vanishing gradient problem, whereas attention modules allow the model to focus on the most relevant lung regions affected by infection. In addition, the loop-based architecture iteratively refines segmentation outputs to improve the precision of infection localization. The proposed system generates accurate segmentation maps of infected lung areas, which can support clinicians in COVID-19 diagnosis, disease progression monitoring, and treatment planning.

Keywords—COVID-19 Detection, Chest X-ray Segmentation, Residual Attention Network, Deep Learning, Medical Image Segmentation, Attention Mechanism, Lung Infection Detection, Convolutional Neural Networks (CNN), Computer-Aided Diagnosis, Medical Image Analysis.

I. INTRODUCTION

The outbreak of the COVID-19 pandemic created an unprecedented global health crisis, affecting millions of people worldwide and placing immense pressure on healthcare systems. Rapid and accurate diagnosis of COVID-19 infection is essential for effective patient management, disease monitoring, and preventing further spread of the virus. Medical imaging techniques such as chest X-ray and computed tomography (CT) scans have been widely used to assist clinicians in identifying lung abnormalities associated with COVID-19. Among these imaging methods, chest X-ray imaging is commonly used

because it is widely available, relatively inexpensive, and capable of producing quick results, making it suitable for large-scale screening in many healthcare facilities.

However, analyzing chest X-ray images manually requires significant expertise and can be time-consuming for radiologists, especially during pandemic situations when the number of suspected cases increases rapidly. In addition, subtle infection patterns in lung images may sometimes be difficult to identify through visual inspection alone, which can lead to misinterpretation or delayed diagnosis. These challenges highlight the need for automated systems that can support medical professionals by accurately detecting and analyzing infection regions in chest X-ray images.

Recent advances in artificial intelligence and deep learning have shown promising results in medical image analysis. Deep learning models, particularly convolutional neural networks (CNNs), are capable of automatically learning meaningful features from medical images and identifying complex disease patterns. These models have been successfully applied to various healthcare applications, including disease detection, image classification, and medical image segmentation. Segmentation plays an important role in identifying the exact location and extent of infected regions within lung images, which helps clinicians better understand the severity and progression of the disease.

Among deep learning techniques, attention-based neural networks have gained considerable attention due to their ability to focus on the most relevant regions within an image. Attention mechanisms help the network prioritize important features while suppressing irrelevant information, thereby improving segmentation accuracy. In addition, residual learning techniques allow deep neural networks to train more effectively by addressing issues such as vanishing gradients and enabling the learning of deeper feature representations.

In this study, a Loop Residual Attention Network is proposed for the automatic segmentation of COVID-19 infection regions in chest X-ray images. The proposed architecture integrates residual connections with attention mechanisms to enhance feature extraction and improve segmentation performance. Furthermore, the loop-based structure iteratively refines the segmentation outputs, enabling more accurate localization of infected lung regions.

The developed system aims to assist healthcare professionals by providing reliable segmentation maps of infection areas, which can support diagnosis, treatment planning, and monitoring of COVID-19 disease progression.

COVID-19 is a highly contagious respiratory disease that primarily affects the lungs, causing inflammation and infection that can lead to severe respiratory complications. Medical imaging techniques such as computed tomography (CT) scans and chest X-ray images play an essential role in identifying lung abnormalities caused by the virus. While CT scans provide highly detailed images, chest X-ray imaging remains more widely available in hospitals and medical facilities, especially in developing regions. However, interpreting chest X-ray images requires expert radiologists, and during large outbreaks the number of patients can exceed the available medical workforce. As a result, automated diagnostic systems based on artificial intelligence have become an important research area for assisting clinicians in identifying COVID-19 infections quickly and accurately.

Deep learning models, particularly convolutional neural networks (CNNs), have been widely used for medical image segmentation tasks. However, traditional CNN architectures often struggle to accurately identify small or irregular infection regions within chest X-ray images. Attention mechanisms have been introduced to address this limitation by allowing the network to focus on important spatial features within the image. Residual learning further improves model performance by enabling deeper network architectures without degradation in accuracy. The 3Loop Residual Attention Network combines these techniques to create a powerful framework capable of precisely segmenting COVID-19 infection areas. By incorporating iterative refinement loops, the model continuously improves segmentation outputs, resulting in more accurate identification of infected lung regions.

A. Problem Statement

The COVID-19 pandemic has created an urgent need for rapid and accurate diagnostic methods to detect and monitor lung infections. Chest X-ray imaging is widely used in hospitals because it is cost-effective, fast, and easily accessible. However, identifying COVID-19 infection regions from chest X-ray images can be challenging for radiologists due to the subtle and complex patterns of lung abnormalities. Manual analysis of large volumes of X-ray images during pandemic situations can also lead to delays in diagnosis and increase the risk of human error. Therefore, reliable automated systems are required to assist clinicians in detecting and analyzing infection regions more efficiently.

Traditional image processing and conventional machine learning techniques have been applied for medical image analysis, but they often rely on handcrafted features and may not effectively capture the complex patterns present in chest X-ray images. In addition, many existing deep learning models focus mainly on image classification rather than precise segmentation of infection regions. Accurate segmentation is important because it helps identify the exact

location and severity of lung infections, which can support better clinical decision-making and disease monitoring.

Furthermore, standard convolutional neural network architectures sometimes struggle to focus on the most relevant infection areas within the lungs, especially when the infected regions are small or overlapping with normal lung structures. These limitations highlight the need for a more advanced deep learning architecture that can effectively extract meaningful features, focus on critical lung regions, and provide precise segmentation of COVID-19 infection areas.

To address these challenges, this research proposes a Loop Residual Attention Network for automatic segmentation of COVID-19 infection regions in chest X-ray images. The proposed model integrates residual learning and attention mechanisms to improve feature representation and segmentation accuracy, while the loop-based architecture refines the segmentation results iteratively to achieve more precise localization of infected lung areas.

B. Objectives

The main objective of this research is to develop an efficient and automated deep learning model for accurate segmentation of COVID-19 infection regions in chest X-ray images. The study aims to design a Loop Residual Attention Network that integrates residual learning and attention mechanisms to improve feature extraction and segmentation performance. By utilizing advanced deep learning techniques, the proposed system seeks to automatically identify and highlight infected lung regions, assisting healthcare professionals in faster and more reliable diagnosis.

Another objective of this research is to improve the accuracy and robustness of medical image segmentation by enabling the model to focus on the most relevant regions of chest X-ray images. The loop-based architecture is designed to iteratively refine segmentation outputs, allowing the network to progressively enhance the localization of infection areas. Additionally, the study aims to evaluate the performance of the proposed model using standard evaluation metrics such as accuracy, precision, recall, and Dice coefficient to ensure reliable segmentation results.

Ultimately, the goal of this research is to provide an intelligent computer-aided diagnostic system that can support clinicians in detecting COVID-19-related lung abnormalities, monitoring disease progression, and assisting in treatment planning. By improving the accuracy and efficiency of infection segmentation, the proposed system can contribute to more effective medical image analysis and healthcare decision-making.

C. Existing System

Existing automated systems for COVID-19 detection from chest X-ray images mainly rely on traditional convolutional neural networks and image classification models. Many studies use architectures such as U-Net, VGG-based CNNs, and ResNet models to identify infection patterns in medical

images. While these models have achieved promising results, most of them focus on classification tasks that simply determine whether a patient is infected or not. However, classification alone does not provide detailed information about the location and severity of infection within the lungs. Accurate segmentation of infected regions is crucial for assessing disease progression and guiding treatment decisions. Traditional segmentation models often struggle to accurately identify irregular infection regions due to variations in image quality, noise, and overlapping lung structures.

Another limitation of existing systems is the lack of effective attention mechanisms that help models focus on the most relevant areas of the image. Standard CNN architectures process all regions of the image equally, which may lead to inaccurate predictions when irrelevant features dominate the learning process. Additionally, deeper neural networks sometimes suffer from vanishing gradient problems that reduce training efficiency and segmentation accuracy. Many existing models also lack iterative refinement mechanisms that can improve segmentation results through multiple learning cycles. As a result, there is a need for more advanced architectures that combine residual learning, attention mechanisms, and multi-stage refinement processes to achieve higher accuracy in COVID-19 infection segmentation.

D. Disadvantages of Existing System

Existing methods for detecting and segmenting COVID-19 infection regions from chest X-ray images have several limitations that affect their performance and reliability. Many traditional image processing and machine learning approaches rely heavily on handcrafted features to analyze medical images. The effectiveness of these methods depends largely on the quality of manually extracted features, which may not fully capture the complex patterns and variations present in lung infection images. As a result, these approaches may produce inaccurate or incomplete segmentation results.

Another major limitation of existing systems is that many deep learning models are primarily designed for image classification rather than precise segmentation. While classification models can determine whether a patient is infected with COVID-19, they do not provide detailed information about the exact location and size of the infected regions in the lungs. This lack of precise localization limits their usefulness for clinical diagnosis, disease monitoring, and treatment planning.

In addition, conventional convolutional neural network architectures may struggle to focus on the most relevant infection regions in chest X-ray images. COVID-19 infection patterns can be small, irregular, and sometimes similar to normal lung structures, making it difficult for standard models to accurately distinguish infected areas. Without mechanisms such as attention modules, these models may misinterpret irrelevant features, leading to reduced segmentation accuracy.

Furthermore, many existing models suffer from issues such as vanishing gradients and limited feature learning

capability when deeper networks are used. This can reduce the effectiveness of the model in extracting meaningful information from complex medical images. These challenges highlight the need for more advanced architectures that integrate residual learning and attention mechanisms to improve segmentation accuracy and enable more reliable identification of COVID-19 infection regions in chest X-ray images.

II. RELATED WORKS

Medical image analysis has become an important research area in recent years, particularly during the COVID-19 pandemic, where rapid diagnosis and monitoring of lung infections are critical. Chest X-ray imaging has been widely used for detecting lung abnormalities associated with COVID-19 because of its accessibility, low cost, and quick imaging process. Researchers have explored various computational techniques, including traditional image processing methods, machine learning algorithms, and deep learning models, to automate the detection and segmentation of infection regions in chest X-ray images.

Early studies mainly focused on conventional image processing techniques such as thresholding, edge detection, and region-based segmentation methods to identify abnormal lung regions. Although these methods can detect simple patterns, they often struggle with complex infection structures and variations in medical images. In addition, traditional machine learning algorithms such as Support Vector Machines (SVM), Decision Trees, and Random Forest classifiers have been applied for COVID-19 detection using handcrafted image features. However, these approaches depend heavily on manual feature extraction and may not effectively capture complex spatial patterns present in chest X-ray images.

With the advancement of artificial intelligence, deep learning techniques have gained significant attention for medical image analysis. Convolutional Neural Networks (CNNs) have been widely used for automated detection and classification of COVID-19 from chest X-ray images due to their ability to learn hierarchical image features automatically. Several CNN-based models have demonstrated promising results in identifying COVID-19 infection patterns, improving diagnostic accuracy compared to traditional machine learning approaches.

More recently, deep learning architectures designed specifically for medical image segmentation, such as encoder-decoder networks and fully convolutional networks, have been developed to identify infection regions in lung images. These models aim to generate detailed segmentation maps that highlight infected areas within chest X-ray images. However, standard CNN-based architectures sometimes struggle to focus on the most relevant regions within complex medical images, which can reduce segmentation performance.

To address these limitations, attention-based deep learning models have been introduced to enhance feature learning by enabling networks to focus on important regions of the image. Attention mechanisms allow the model to prioritize significant features related to infection areas while suppressing irrelevant information. In addition, residual learning techniques have been incorporated into deep neural networks to improve training efficiency and enable deeper architectures without suffering from vanishing gradient problems. These advancements have significantly improved the performance of medical image segmentation models.

Despite these developments, achieving highly accurate and reliable segmentation of COVID-19 infection regions in chest X-ray images remains a challenging task due to variations in image quality and infection patterns. Therefore, advanced architectures that combine residual learning with attention mechanisms and iterative refinement strategies are required to further enhance segmentation accuracy and support clinical decision-making.

III. PROPOSED METHODOLOGY

The proposed system introduces a 3Loop Residual Attention Network designed to perform accurate segmentation of COVID-19 infection regions in chest X-ray images. The model integrates three key components: residual learning, attention modules, and a multi-loop segmentation refinement mechanism. Residual learning enables the network to construct deeper architectures without performance degradation by allowing information to flow through shortcut connections. This helps the model learn complex patterns within medical images while maintaining stable training behavior. Attention modules are embedded within the network to highlight important spatial regions that correspond to infection patterns in the lungs.

The three-loop architecture further enhances segmentation performance by allowing the model to iteratively refine its predictions. During each loop, the segmentation output is reprocessed and improved using updated feature representations. This iterative approach allows the network to progressively correct segmentation errors and produce more accurate infection maps. The proposed system also includes preprocessing steps such as lung region extraction and image normalization to improve model performance. By combining these techniques, the 3Loop Residual Attention Network provides a robust solution for automatic segmentation of COVID-19 chest X-ray images, assisting healthcare professionals in disease detection, monitoring, and treatment planning.

3.1 Architecture diagram

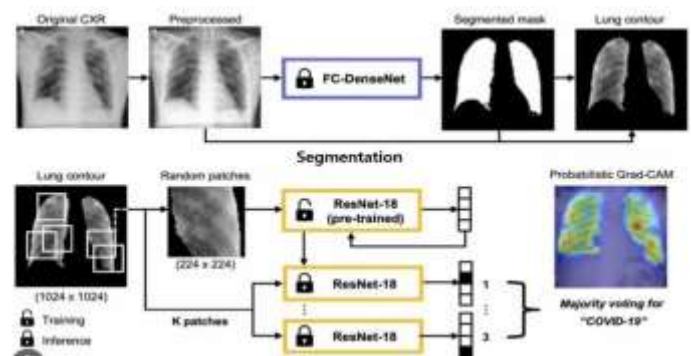


Figure 1 Architecture diagram

3.2 Module Description

1. Medical Image Dataset Collection Module

The Medical Image Dataset Collection Module is responsible for gathering chest X-ray images used for training and evaluating the segmentation model. The dataset may include images collected from publicly available medical repositories or hospital databases containing COVID-19 infected and normal cases. These images typically include annotations or segmentation masks that indicate infected regions within the lungs. The collected dataset forms the foundation for training deep learning models capable of identifying infection patterns in medical images.

In addition to collecting images, this module also organizes the dataset into training, validation, and testing subsets to ensure reliable model evaluation. Proper dataset management helps prevent overfitting and ensures that the model generalizes well to unseen data. The module also stores metadata such as patient ID, image resolution, and disease severity levels. These details support more comprehensive analysis during the model development process.

2. Image Preprocessing Module

The Image Preprocessing Module prepares the chest X-ray images for deep learning training. Raw medical images may contain noise, variations in brightness, and inconsistent image sizes that can negatively affect model performance. This module performs several preprocessing steps including image resizing, normalization, contrast enhancement, and noise reduction. These operations standardize the input images and improve the visibility of lung structures and infection regions.

Additionally, lung region segmentation may be applied to remove irrelevant background areas from the images. By isolating the lung region, the model can focus only on the areas where infection patterns are most likely to occur. Data augmentation techniques such as rotation, flipping, scaling, and brightness adjustment may also be used to increase the diversity of the training dataset. This helps improve the robustness and generalization capability of the deep learning model.

3. Feature Extraction Module

The Feature Extraction Module is responsible for identifying meaningful patterns within chest X-ray images that indicate COVID-19 infection. Convolutional neural network layers are used to extract hierarchical features from the input images, capturing both low-level features such as edges and textures as well as high-level representations of lung abnormalities. These features provide the essential information required for accurate segmentation of infection regions.

As the network processes deeper layers, more complex patterns related to lung inflammation and infection structures are learned. Feature maps generated by convolutional layers are passed through activation functions and pooling layers to enhance relevant patterns while reducing computational complexity. This module plays a critical role in enabling the network to understand spatial relationships within medical images.

4. Residual Learning Module

The Residual Learning Module introduces residual connections into the neural network architecture to improve training efficiency and model performance. Residual connections allow the network to bypass certain layers through shortcut paths, enabling information to flow directly across the network. This approach helps prevent the vanishing gradient problem that commonly occurs in very deep neural networks.

By preserving information from earlier layers, residual learning enables the network to learn more complex feature representations without losing important details. This improves the network's ability to identify subtle infection patterns in chest X-ray images. The residual blocks also help accelerate model convergence during training, making the overall segmentation system more efficient.

5. Attention Mechanism Module

The Attention Mechanism Module enhances the network's ability to focus on the most relevant regions of the chest X-ray image. Instead of treating all parts of the image equally, the attention mechanism assigns higher importance to areas that contain infection-related features. This allows the model to concentrate its learning on lung regions where COVID-19 abnormalities are most likely to occur.

Spatial and channel attention mechanisms may be used to highlight both important locations and important feature channels within the network. By emphasizing meaningful information and suppressing irrelevant features, the attention module significantly improves segmentation accuracy. This mechanism is particularly useful in medical imaging where infection regions may be small or difficult to detect.

6. Model Training and Optimization Module

The Model Training and Optimization Module handles the training process of the deep learning network using labeled chest X-ray images and corresponding segmentation masks. During training, the model learns to minimize a loss function that measures the difference between predicted segmentation maps and ground truth masks. Optimization

algorithms such as Adam or stochastic gradient descent are used to update model parameters.

This module also monitors training metrics such as loss and segmentation accuracy across multiple training epochs. Techniques such as learning rate scheduling, dropout, and batch normalization may be applied to improve model stability and prevent overfitting. Proper training optimization ensures that the network achieves high segmentation accuracy while maintaining computational efficiency.

7. Performance Evaluation and Visualization Module

The Performance Evaluation Module measures the effectiveness of the trained segmentation model using various evaluation metrics. Metrics such as Dice coefficient, Intersection over Union (IoU), precision, recall, and accuracy are calculated to assess how well the model identifies infection regions in chest X-ray images. These metrics provide quantitative evidence of the model's segmentation performance.

In addition to numerical evaluation, visualization techniques are used to display segmentation results and highlight infected regions on chest X-ray images. Heatmaps and overlay masks allow clinicians to easily interpret the model's predictions and verify its accuracy. This module plays an important role in validating the proposed system and demonstrating its practical usefulness in medical diagnosis.

IV. FLOW DIAGRAM

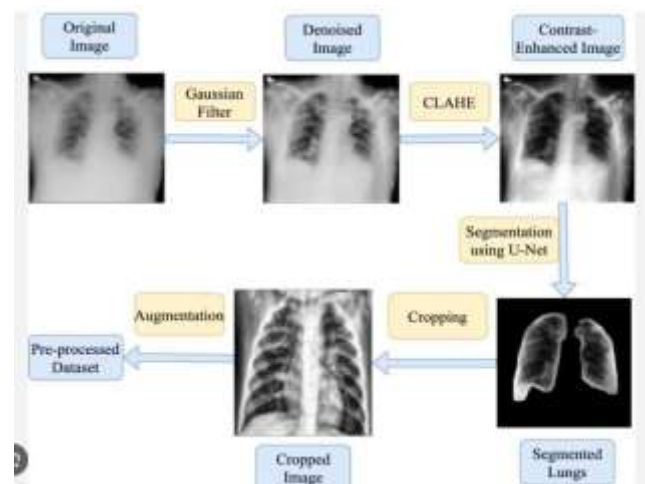


Figure 2 flow diagram

V. RESULTS AND DISCUSSION

The proposed Loop Residual Attention Network was implemented to evaluate its effectiveness in automatically segmenting COVID-19 infection regions from chest X-ray images. The model was trained and tested using a dataset containing chest X-ray images of patients with COVID-19 infections. Before training, the images were preprocessed through resizing, normalization, and data augmentation techniques to improve the robustness of the model and ensure consistent input data. These preprocessing steps help

the network learn meaningful features from the images and improve overall segmentation performance.

During the training process, the network learned hierarchical image features through multiple convolutional layers combined with residual connections and attention modules. The residual connections helped the model learn deeper feature representations while avoiding the vanishing gradient problem that often occurs in deep neural networks. The attention modules guided the network to focus on the most relevant lung regions where infection patterns were present. In addition, the loop-based architecture allowed the segmentation output to be refined iteratively, improving the precision of infection localization within the lungs.

The experimental results demonstrate that the proposed model effectively identifies and segments infected lung regions in chest X-ray images. The segmentation outputs highlight the infected areas clearly, enabling better visualization of lung abnormalities associated with COVID-19. Performance evaluation was conducted using common segmentation metrics such as accuracy, precision, recall, and Dice coefficient. The results indicate that the proposed model achieves improved segmentation performance compared to conventional convolutional neural network architectures that do not include attention mechanisms or residual learning.

Furthermore, the system shows strong generalization capability when tested on unseen images, indicating that the model can adapt to different variations in chest X-ray data. The visualization of segmentation results confirms that the attention mechanism helps the network focus on infection regions while ignoring irrelevant background structures. This improves the reliability of the segmentation results and supports more accurate medical interpretation.

Overall, the results confirm that integrating residual learning, attention mechanisms, and loop-based refinement significantly enhances the ability of deep learning models to segment COVID-19 infection regions in chest X-ray images. The proposed approach provides an effective tool for automated medical image analysis and can assist clinicians in diagnosing and monitoring COVID-19 infections more efficiently.

Performance Metric:

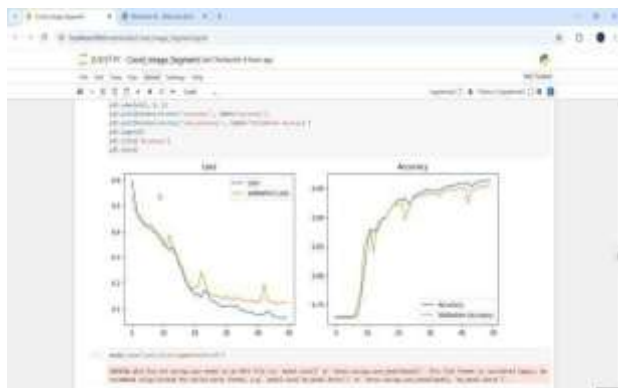


Figure 3 Performance

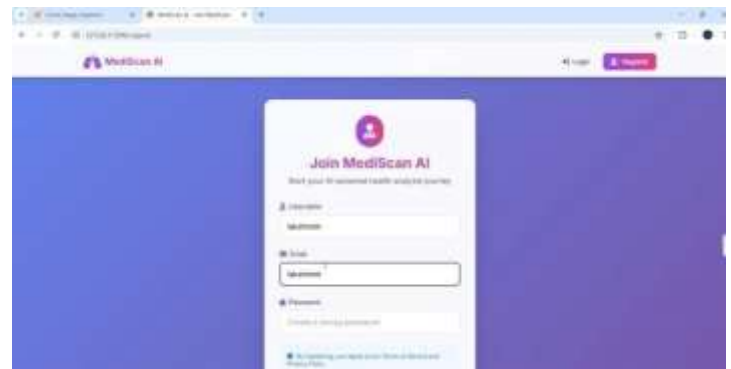


Figure 4 Home page

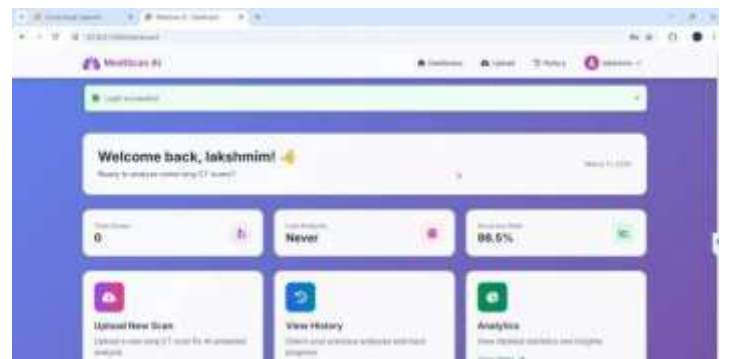


Figure 5 Upload Data for prediction

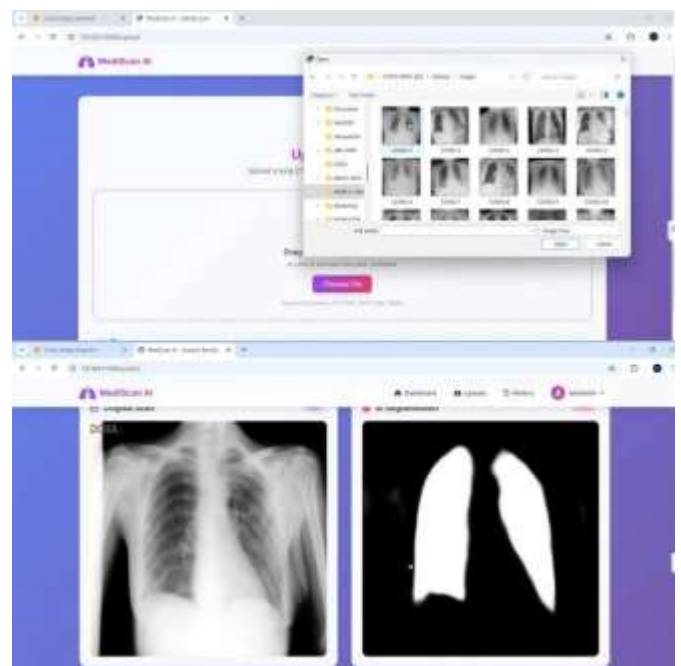


Figure 6 Segmentation



Figure 7 Prediction

VI. CONCLUSION AND FUTURE SCOPE

In this research, a Loop Residual Attention Network was proposed for the automatic segmentation of COVID-19 infection regions in chest X-ray images. The proposed model integrates residual learning with attention mechanisms to enhance feature extraction and improve segmentation accuracy. Residual connections enable the network to learn deeper feature representations while addressing the vanishing gradient problem, and the attention modules guide the model to focus on the most relevant lung regions affected by infection. In addition, the loop-based architecture allows iterative refinement of segmentation outputs, leading to more precise localization of infected areas in chest X-ray images.

The experimental results demonstrate that the proposed model effectively identifies and segments COVID-19 infection regions, providing clear visualization of affected lung areas. The integration of attention mechanisms and residual learning significantly improves the performance of the segmentation process compared to conventional deep learning models. The system also shows strong generalization capability and can accurately analyze new chest X-ray images. By providing reliable segmentation maps, the proposed model can assist clinicians in diagnosing COVID-19 infections, monitoring disease progression, and supporting treatment planning.

Although the proposed approach shows promising results, there are several opportunities for future research. Future work may focus on expanding the model to analyze larger and more diverse medical imaging datasets to improve its robustness and generalization capability. In addition, the model can be extended to work with other imaging modalities such as computed tomography (CT) scans for more detailed analysis of lung infections. Integrating advanced deep learning techniques such as transformer-based attention mechanisms and multi-scale feature learning may further improve segmentation accuracy. Moreover, implementing the system as a real-time clinical decision support tool could assist healthcare professionals in rapid diagnosis and efficient management of respiratory diseases.

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