ENABLING PRECISE DIAGNOSIS: CXRNet FOR PNEUMONIA DETECTIONWITH ENHANCED VISUAL EXPLANATIONS

A PROJECT REPORT

Submitted by

AAKASH K (202009001)

YASWANTH B (202009047)

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BONAFIDE CERTIFICATE

This is to certify that this project report **"ENABLING PRECISE DIAGNOSIS: CXRNet FOR PNEUMONIA DETECTION WITH ENHANCED VISUAL** EXPLANATIONS OF FEATURES" **is the bonafide work of** "AAKASH K (Reg. No.: 202009001), YASWANTH B (Reg. No.: 202009047)" who carried out the project work under my supervision.

SIGNATURE
Dr. J.Angela Jennifa Sujana
HEAD OF THE DEPARTMENT
Professor & Head
Artificial Intelligence & Data Science Department
Mepco Schlenk Engg. College, Sivakasi
Virudhunagar Dt. – 626 005

SIGNATURE
Dr. A. SHENBAGARAJAN
SUPERVISOR
Associate Professor
Artificial Intelligence & Data Science Department
Mepco Schlenk Engg. College, Sivakasi
Virudhunagar Dt. – 626 005

Submitted to the Viva-Voce examination held on ___/__/____.

INTERNAL EXAMINER

EXTERNAL EXAMINER

ABSTRACT

Accurate detection of pneumonia is crucial in the context of the global pandemic, where swift and precise diagnosis can mean the difference between effective treatment and potentially dire outcomes. At the time of chest X-ray (CXR) imaging has long been recognized for its speed and accessibility, current deep learning models often lack transparency in their decision- making processes, limiting their practical utility in clinical settings. Then, in response to this challenge, a groundbreaking study introduces CXRNet, a novel approach engineered specifically for the precise detection of pneumonia, while also providing transparent explanations derived directly from CXR images. CXRNet represents a significant departure from conventional deep learning architectures, leveraging an innovative Encoder-Decoder-Encoder framework bolstered by an additional encoder dedicated to training. This unique architecture allows CXRNet to achieveexceptional performance across a wide spectrum of CXR datasets, ranging from those representinghealthy individuals to those encompassing cases of bacterial and viral pneumonia, including the distinctive characteristics associated with COVID-19 pneumonia. The results of the study not onlyunderscore CXRNet's impressive accuracy but also highlight its ability to generate detailed activation maps, these serve as invaluable aids in the intuitive interpretation of lung disease detection. One of the most compelling aspects of CXRNet lies in its capacity to provide clear and concise explanations for its diagnostic decisions, a feature that sets it apart from existing methodsand enhances its utility in clinical practice. Moreover, CXRNet's adaptability to diverse computing environments enhances its feasibility for real-world implementation, ensuring its accessibility across a broad spectrum of healthcare facilities. Furthermore, the inclusion of detailed activation maps generated by CXRNet not only enhances diagnostic confidence but also empowers healthcare professionals to make more accurate assessments, thereby improving patient outcomes. With its demonstrated versatility across various CXR datasets, including complex cases such as viral and COVID-19 pneumonia, CXRNet emerges as a robust and reliable solution for precise lung disease diagnosis which is user friendly and cost efficient.

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LIST OF ABBREVIATIONS

ABBREVIATIONS		EXPANSION
CLAHE	--	**C**ontrast **L**imited **A**daptive **H**istogram **E**qualization
CNN	-	**C**onvolutional **N**eural **N**etwork
AI	-	**A**rtificial **I**ntelligence
AUC	-	**A**rea **U**nder the ROC **C**urve
SVM	-	**S**upport **V**ector **M**achine
ACC	-	**A**ccuracy
CGC	-	**C**ustomer **G**enerated **C**ontent
GBM	-	**G**radient **B**oost **M**achines
XAI	-	**E**xplainable **A**rtificial **I**ntelligence
SHAP	-	**SH**apley **A**dditive ex**P**lanations
GRAD-CAM	-	**Gradi**ent-**w**eighted **C**lass **A**ctivation **M**apping

CHAPTER 1

INTRODUCTION

1.1 BACKGROUND AND CONTEXT

In addition to its diagnostic challenges, pneumonia presents significant burdens on healthcare systems worldwide, contributing to substantial morbidity, mortality, and economic costs. Timely and accurate diagnosis is crucial for initiating appropriate treatment interventions, reducing the risk of complications, and improving patient outcomes. However, the interpretation of CXR images for pneumonia diagnosis is often subjective and prone to interobserver variability, highlighting the need for objective and standardized diagnostic approaches. The emergence of deep learning-basedapproaches offers promising opportunities to enhance pneumonia diagnosis by automating image interpretation and providing quantitative assessments of disease severity. Training the CNNs on large datasets of annotated CXR images, these systems can learn to recognize subtle patterns and features indicative of pneumonia, enabling more consistent and reliable diagnoses. Moreover, theintegration of AI-driven diagnostic systems into clinical workflows has the potential to streamlinethe diagnostic process, reduce interpretation times, and alleviate the workload burden on healthcare professionals.

Beyond its diagnostic capabilities, the proposed CXRNet aims to provide enhanced visual explanations of the features contributing to the diagnosis, empowering clinicians with valuable insights into the underlying pathology. By generating visual heatmaps or saliency maps highlighting regions of interest in CXR images, the system can elucidate the rationale behind the diagnostic decision, fostering greater trust and confidence in the automated diagnostic process. Furthermore, the development of CXRNet represents a significant step towards advancing precision medicine in pneumonia diagnosis. By leveraging AI-driven technologies to tailor treatment strategies based on individual patient characteristics and disease severity, clinicians can optimize patient outcomes and resource utilization, ultimately improving the overall quality of carefor patients with pneumonia. Moreover, the adoption of CXRNet and similar AI-driven diagnostic systems has the potential to address disparities in access to healthcare services, particularly in underserved regions or resource-limited settings.

1.2 REDEFINING PNEUMONIA DIAGNOSIS

In the rapidly evolving landscape of healthcare, the demand for innovative solutions to enhance diagnostic accuracy and efficiency in pneumonia diagnosis has become increasingly

urgent. With the advent of cutting-edge technology and advanced machine learning techniques, there exists a profound opportunity to redefine the approach to diagnosing pneumonia. This paradigm shift involves leveraging the capabilities of deep learning algorithms, specifically Convolutional Neural Networks (CNNs), to revolutionize the interpretation of chest X-ray (CXR) images. By training CNNs on vast datasets of annotated CXR images, these systems can learn to recognize intricate patterns and subtle features indicative of pneumonia with remarkable accuracy. This transformative approach not only automates the diagnostic process but also provides quantitative assessments of disease severity, enabling more consistent and reliable diagnoses. Moreover, the integration of AI-driven diagnostic systems into clinical workflows holds the potential to streamline the diagnostic process, reduce interpretation times, and alleviate the workload burden on healthcare professionals. Overall, the redefinition of pneumonia diagnosis through innovative approaches represents a significant advancement in healthcare, promising improved patient outcomes, reduced healthcare costs, and enhanced healthcare equity globally.

1.2.1 Diagnostic Evolution

The evolution of diagnostic paradigms in pneumonia detection reflects a journey marked by continuous innovation and the transformative potential of advanced technologies. Initially, pneumonia diagnosis relied heavily on traditional manual interpretation by radiologists, a process prone to subjectivity and interobserver variability. However, with the advent of digital imaging technologies and the rise of artificial intelligence (AI), significant advancements have reshaped the diagnostic landscape. The introduction of AI-driven diagnostic systems, particularly utilizing deep learning algorithms such as Convolutional Neural Networks (CNNs), has revolutionized pneumonia detection. These systems are trained on extensive datasets of annotated chest X-ray (CXR) images, enabling them to recognize intricate patterns and subtle features indicative of pneumonia with unprecedented accuracy. This shift towards automated image interpretation not only enhances diagnostic efficiency but also provides quantitative assessments of disease severity, empowering clinicians with actionable insights for patient management. Furthermore, the integration of AI-driven diagnostic systems into clinical workflows streamlines the diagnostic process, reduces interpretation times, and alleviates the workload burden on healthcare professionals. As a result, the journey from manual interpretation to AI-driven diagnosis signifies a remarkable advancement in healthcare, promising improved patient outcomes and reduced healthcare.

1.2.2 AI in Medical Imaging

The integration of artificial intelligence (AI) into medical imaging has precipitated a revolutionary transformation in diagnostic capabilities, particularly evident in the domain of pneumonia diagnosis. Through the utilization of deep learning algorithms and access to expansive datasets, AI-driven systems have attained an unprecedented ability to scrutinize complex medical images with remarkable precision and efficiency. This amalgamation of advanced technology and vast data resources has opened pathways for transformative advancements in pneumonia diagnosis, offering solutions to longstanding challenges in interpretation and accuracy. By leveraging the power of AI, these systems can discern subtle patterns and features within chest X-ray (CXR) images that might elude human perception, thereby enhancing diagnostic accuracy and expeditingpatient care. The integration of AI into medical imaging also holds promise for optimizing resource allocation, reducing healthcare costs, and improving patient outcomes. As AI continues to evolve and proliferate within healthcare systems, its role in pneumonia diagnosis is poised to drive further innovation and excellence, shaping the future of medical imaging and diagnostic practices.

1.3 INNOVATING DEEP LEARNING

Innovation lies at the heart of developing deep learning models capable of accurately detecting pneumonia from chest X-ray (CXR) images. This section explores the innovative methodologies and techniques employed in the development of state-of-the-art deep learning architectures for pneumonia diagnosis.

1.3.1 Model Advancements

Advancements in deep learning model architectures, such as convolutional neural networks (CNNs) and attention mechanisms, have revolutionized pneumonia detection. Continually innovating and refining these architectures, researchers strive to enhance diagnostic accuracy and interpretability, driving progress in medical imaging diagnostics. Attention mechanisms represent another innovative approach to model architecture design, enabling deep learning models to dynamically focus on salient regions of input images. Leveraging sophisticated CNN architectures, attention mechanisms, and multimodal integration techniques, researchers continueto push the boundaries of diagnostic accuracy and interpretability, ultimately enhancing the efficacy of AI-driven medical imaging systems in clinical practice.

1.3.2 Interpretable AI

Interpretable AI techniques play a pivotal role in providing healthcare professionals with actionable insights into diagnostic decisions. Through innovative approaches such as attention mechanisms and feature visualization, deep learning models can elucidate the underlying rationale behind pneumonia diagnoses, empowering clinicians with valuable information for patient care. Attention mechanisms represent a key innovation in interpretable AI, enabling deep learning models to selectively focus on relevant regions of input images while filtering out irrelevant information. This not only aids in diagnostic interpretation but also fosters a deeper understanding of disease mechanisms, paving the way for personalized treatment strategies and therapeutic interventions. Fostering the transparency, interpretability, and collaboration, these techniques empower clinicians to make more informed decisions, optimize patient care, and ultimately improve clinical outcomes for individuals with pneumonia and other respiratory conditions.

1.4 PROJECT OBJECTIVES

1.4.1 AI-driven Detection

The primary objective of this project is to develop an advanced AI-driven pneumonia detection system leveraging state-of-the-art deep learning models and innovative interpretability techniques. Harnessing the power of convolutional neural networks (CNNs) and attention mechanisms, the system aims to accurately detect pneumonia from chest X-ray (CXR) images while providing enhanced visual explanations of the features contributing to the diagnosis. The proposed system will not only assist radiologists in making more accurate and timely diagnoses but also help improve patient outcomes by enabling early detection and treatment of pneumonia. Additionally, the interpretability techniques integrated into the system will enhance trust and transparency in the decision-making process, ultimately leading to better acceptance and adoptionof AI technology in healthcare settings.

1.4.2 Clinical Validation

Another objective of this project is to evaluate the clinical utility and translational potentialof the developed pneumonia detection system through rigorous validation studies and real-world deployments. By conducting clinical validation studies, addressing key implementation challenges, and fostering collaboration with healthcare stakeholders, the project seeks to demonstrate the efficacy, safety, and cost-effectiveness of AI technologies in improving diagnostic accuracy, workflow efficiency, and patient outcomes in pneumonia

diagnosis. Through these efforts, the project aims to pave the way for the integration of AI-based pneumonia detection systems into routine clinical practice, ultimately benefiting healthcare providers, patients, and healthcare systems as a whole. By establishing the clinical validity and real-world applicability of the system, this project will contribute to the advancement of AI technologies in healthcare and the delivery of more accurate and timely pneumonia diagnoses.

1.5 PROJECT SCOPE

1.5.1 Model Development

The scope of this project encompasses the development and optimization of deep learning models for pneumonia detection using chest X-ray (CXR) images. This includes exploring innovative model architectures, data preprocessing techniques, and interpretability methods to enhance diagnostic accuracy, reliability, and interpretability. The project also involves fine-tuning pre-trained models, conducting extensive performance evaluations, and benchmarking against existing state-of-the-art methods in the field. Additionally, the research will focus on addressing challenges such as class imbalance, data augmentation, and transfer learning to improve the generalization capabilities of the models. Through rigorous experimentation and analysis, the goalis to push the boundaries of pneumonia detection using deep learning technology and contribute valuable insights to the medical imaging community.

1.5.2 Clinical Validation

Furthermore, the project aims to conduct clinical validation studies to assess the performance and impact of the developed pneumonia detection system in real-world clinical settings. This involves collaborating with healthcare institutions, regulatory agencies, and industry partners to navigate regulatory compliance, reimbursement policies, and implementation challenges, ultimately facilitating the translation and adoption of AI technologies into routine clinical workflows. The project team will also work closely with healthcare providers to ensure seamless integration of the pneumonia detection system into existing clinical processes, as well as provide training and support to enhance user acceptance and satisfaction. By engaging stakeholders at every stage of the development and implementation process, the project aims to maximize the system's impact on patient outcomes and healthcare delivery.

1.6 SIGNIFICANCE AND IMPACT

1.6.1 Diagnostic Advancements:

The project holds significant implications for advancing diagnostic capabilities in

respiratory care, particularly in the timely and accurate detection of pneumonia. By developing anAI-driven pneumonia detection system with enhanced interpretability, the project aims to empower healthcare professionals with actionable insights into diagnostic decisions, ultimately improving patient outcomes and enhancing clinical decision-making in pneumonia diagnosis and management. The system's integration of cutting-edge machine learning algorithms and advancedimaging techniques promises to revolutionize the way pneumonia is diagnosed and treated, offering a more efficient and reliable approach to healthcare delivery. Through seamless collaboration between technology and medical expertise, this innovative solution is poised to set new standards in respiratory care, paving the way for a future where precision medicine and AI- driven diagnostics work hand in hand to save lives and improve patient well-being.

1.6.2 AI Adoption:

Furthermore, the project has the potential to catalyze the adoption of artificial intelligence (AI) technologies in healthcare by demonstrating the clinical utility and translational potential of AI-driven diagnostic systems. By conducting rigorous validation studies, addressing key implementation challenges, and fostering collaboration between researchers, clinicians, and healthcare stakeholders, the project seeks to pave the way for the widespread integration of AI technologies into routine clinical practice, ultimately revolutionizing the diagnosis and management of respiratory illnesses like pneumonia. Moreover, the project aims to enhance the efficiency and accuracy of diagnostic processes, reduce healthcare costs, and improve patient outcomes. By harnessing the power of AI to analyze complex medical data and images, healthcare providers can make more informed decisions, leading to earlier detection of diseases and personalized treatment plans. With the potential to revolutionize the way healthcare is delivered, this project represents a significant step forward in the field of AI-driven healthcare innovation.

CHAPTER 2

LITERATURE SURVEY

1. Amira Ouerhani, Souhaila Boulares, Halima Mahjoubi , "Automated Detection of Paediatric Pneumonia from Chest X-Ray Images Using Deep Learning Models" , 2023 IEEE Afro-Med-iterranean Conference on Artificial Intelligence (AMCAI)

In this study, Amira Ouerhani, Souhaila Boulares, and Halima Mahjoubi presented an investigation into the automated detection of pediatric pneumonia from chest X-ray images utilizing deep learning models. Prior research in this domain has highlighted the significance of accurate and timely diagnosis of pneumonia, particularly in pediatric patients, to enhance treatment outcomes and reduce mortality rates. The authors emphasized the growing interest in leveraging advanced machine learning techniques, specifically deep learning models, to develop automated systems capable of accurately identifying pneumonia from medical imaging data. They noted a variety of deep learning architectures previously explored for medical image analysis tasks, including convolutional neural networks (CNNs) and their variants, recurrent neural networks (RNNs), and more recent advancements such as attention mechanisms and transfer learning strategies. Additionally, the authors highlighted the challenges associated with pediatric pneumonia diagnosis, including the variability in chest X-ray images due to factors such as patient age, positioning, and underlying conditions. They underscored the importance of large-scale datasets annotated by expert radiologists for training robust deep learning models capable of generalizing across diverse patient populations and imaging conditions. Furthermore, the authors discussed the potential impact of automated pneumonia detection systems in clinical practice, including facilitating timely diagnosis, reducing diagnostic errors, and improving healthcare resource allocation. Through their study, Ouerhani, Boulares, and Mahjoubi aimed to contribute to the ongoing efforts in leveraging artificial intelligence for improving healthcare outcomes, particularly in the context of pediatric pneumonia diagnosis.

2. Kanwarpartap Singh Gill; Vatsala Anand; Rahul Chauhan; Devyani Rawat; Rupesh Gupta ,"Using Deep Learning and MobileNet50V2 CNN Model to Classify Chest X-Ray Images forPneumonia Disease Detection" ,2023 2nd International Conference on Futuristic Technolo- gies (INCOFT)

In this study, Kanwarpartap Singh Gill, Vatsala Anand, Rahul Chauhan, Devyani Rawat, and Rupesh Gupta investigated the utilization of deep learning techniques, specifically the

MobileNetV2 CNN model, for the classification of chest X-ray images to detect pneumonia disease. The authors contextualized their research within the broader landscape of computer-aided diagnosis systems aimed at improving the efficiency and accuracy of medical image analysis tasks. Previous studies have demonstrated the potential of convolutional neural networks (CNNs) in effectively learning discriminative features from medical images and facilitating automated disease diagnosis. Gill et al. highlighted the significance of pneumonia detection, emphasizing the importance of timely diagnosis and treatment to mitigate the associated morbidity and mortality rates. They discussed the limitations of traditional diagnostic methods and the growing interest in leveraging deep learning models to enhance diagnostic accuracy and efficiency. The authors introduced the MobileNetV2 architecture, which is specifically designed for resource-constrained environments such as mobile devices, making it suitable for deployment in real-world healthcare settings. They elaborated on the architectural features of MobileNetV2, including depthwise separable convolutions and inverted residuals, which contribute to its efficiency and effectiveness in image classification tasks. Furthermore, Gill and colleagues discussed the challenges associated with training deep learning models for medical image analysis, including the requirement for large annotated datasets and the need for robust evaluation metrics to assess model performance. Through their study, the authors aimed to contribute to the development of reliable and scalable AI-based solutions for pneumonia detection, with potential applications in clinical settings for improving patient care and healthcare outcomes.

3. Anis Amirah Binti Ramli; Zalikha Zulkifli; Samsiah Ahmad; Nurulhuda Ghazali, "Auto- matic Pneumonia Detection Through Chest X-Ray Image-Based" ,2023 4th International Conference on Artificial Intelligence and Data Sciences (AiDAS)

In this study, Anis Amirah Binti Ramli, Zalikha Zulkifli, Samsiah Ahmad, and Nurulhuda Ghazali explored automatic pneumonia detection through chest X-ray image analysis. The authors situated their research within the broader context of leveraging artificial intelligence (AI) and image processing techniques to enhance medical diagnosis, particularly in the domain of pulmonary diseases. Previous research has highlighted the potential of machine learning and deep learning algorithms in analyzing medical images to assist healthcare professionals in accurate disease detection and classification. Ramli et al. emphasized the significance of pneumonia detection, considering its prevalence and impact on public health worldwide. They discussed the limitations of manual interpretation of chest X-ray images, including subjectivity and variability among radiologists, underscoring the need for automated

systems to support clinical decision-making processes. The authors introduced their approach to automatic pneumonia detection, which involves preprocessing of chest X-ray images followed by feature extraction and classification using machine learning algorithms. They elaborated on the image processing techniques employed to enhance the quality and relevance of extracted features, including image normalization, noise reduction, and edge detection. Additionally, Ramli and colleagues discussed the selection and optimization of machine learning models for pneumonia classification, considering factors such as model complexity, generalization ability, and computational efficiency. They highlighted the importance of training datasets comprising diverse chest X-ray images annotated by experienced radiologists to ensure the robustness and reliability of the developed system. Through their study, the authors aimed to contribute to the ongoing efforts in developing AI-based solutions for pneumonia detection, with potential applications in clinical settings for improving diagnostic accuracy and patient care.

4. Orestis Papadimitriou; Athanasios Kanavos; Manolis Maragoudakis, "Automated Pneumo- nia Detection from Chest X-Ray Images Using Deep Convolutional Neural Networks",2023 14th International Conference on Information, Intelligence, Systems & Applications (IISA)

In this study, Orestis Papadimitriou, Athanasios Kanavos, and Manolis Maragoudakis investigated the automated detection of pneumonia from chest X-ray images employing deep convolutional neural networks (CNNs). The authors contextualized their research within the realm of computer-aided diagnosis systems, emphasizing the potential of deep learning techniques to enhance the efficiency and accuracy of medical image analysis tasks. Previous studies have demonstrated the effectiveness of CNNs in learning discriminative features from complex image data, making them well-suited for automated disease detection in medical imaging. Papadimitriou et al. underscored the significance of pneumonia detection, considering its clinical importance and the challenges associated with manual interpretation of chest X-ray images by radiologists. They discussed the limitations of traditional diagnostic methods and the need for reliable and scalable AI-based solutions to assist healthcare professionals in timely and accurate disease diagnosis. The authors introduced their approach to automated pneumonia detection, which involves preprocessing of chest X-ray images, followed by feature extraction and classification using deep CNN architectures. They elaborated on the architectural design and training strategies employed for the deep CNN model, emphasizing the importance of data augmentation techniques and transfer learning to

improve model generalization and robustness. Furthermore, Papadimitriou and colleagues discussed the evaluation metrics used to assess the performance of the developed system, including accuracy, sensitivity, specificity, and area under the receiver operating characteristic curve (AUC-ROC). Through their study, the authors aimed to contribute to the advancement of AI-based solutions for pneumonia detection, with potential applications in clinical practice for improving diagnostic efficiency and patient outcomes.

5. Anika Bushra; Mohammad Ashfak Habib; Md. Jahidul Hasan Jahid, "COVID-19 Detection from Chest X-ray Images Using Deep Learning Approach",2023 26th International Conferenceon Computer and Information Technology (ICCIT)

In this study, Anika Bushra, Mohammad Ashfak Habib, and Md. Jahidul Hasan Jahid investigated the detection of COVID-19 from chest X-ray images utilizing a deep learning approach. The authors situated their research within the context of the urgent need for effective diagnostic tools amidst the COVID-19 pandemic, highlighting the potential of deep learning techniques to aid in the rapid and accurate identification of the disease from medical imaging data. Previous studies have underscored the challenges associated with traditional diagnostic methods for COVID-19, including the limited availability and variability of reverse transcription-polymerase chain reaction (RT-PCR) tests. Bushra et al. emphasized the importance of chest X-ray imaging as a complementary diagnostic modality, particularly in resource-constrained settings where access to RT-PCR testing may be limited. They discussed the characteristic features of COVID-19 pneumonia observed in chest X-ray images, such as ground-glass opacities and consolidations, which can be leveraged for automated disease detection using deep learning models. The authors introduced their deep learning approach, which encompasses preprocessing of chest X-ray images followed by feature extraction and classification using convolutional neural networks (CNNs). They elaborated on the architectural design and training strategies employed for the CNN model, stressing the significance of data augmentation techniques and model optimization to enhance performance. Furthermore, Bushra and colleagues discussed the evaluation metrics utilized to assess the effectiveness of the developed system, including sensitivity, specificity, and area under the receiver operating characteristic curve (AUC-ROC).

6. Poonam Shourie; Vatsala Anand; Sheifali Gupta, "An Efficient CNN Framework for Radiol- ogist level Pneumonia Detection Using Chest X-ray Images" ,2023 3rd International Conferenceon Intelligent Technologies (CONIT)

In this study, Poonam Shourie, Vatsala Anand, and Sheifali Gupta presented an efficient convolutional neural network (CNN) framework for radiologist-level pneumonia detection using chest X-ray images. The authors addressed the pressing need for accurate and efficient pneumonia detection methods to assist radiologists in clinical practice, particularly in scenarios where expert interpretation may be limited or unavailable. Shourie et al. acknowledged the challenges associated with manual interpretation of chest X-ray images and the potential for deep learning techniques to augment radiologist performance. They emphasized the importance of developing CNN models capable of achieving performance levels comparable to experienced radiologists, thereby enhancing diagnostic accuracy and efficiency. The authors introduced their CNN framework, which involves preprocessing of chest X-ray images followed by feature extraction and classification using a deep CNN architecture. They elaborated on the design choices and optimization strategies employed to ensure the efficiency and effectiveness of the proposed framework, highlighting the incorporation of transfer learning and fine-tuning techniques to leverage pre-trained models and adapt them to the task of pneumonia detection. Furthermore, Shourie and colleagues discussed the evaluation methodology utilized to assess the performance of their CNN framework, including metrics such as sensitivity, specificity, and area under the receiver operating characteristic curve (AUC-ROC). Through their study, the authors aimed to contribute to the development of robust and reliable AI-based solutions for pneumonia detection, potentially aiding radiologists in clinical decision-making processes and improving patient outcomes.

7. Advait Gupta; Manan Padsala; Pallabi Saikia, "Detection of Pneumonia from Chest X-Ray Images Using Transfer Learning on Deep CNN" ,2023 4th International Conference for Emerg-ing Technology (INCET)

In this study, Advait Gupta, Manan Padsala, and Pallabi Saikia investigated the detection of pneumonia from chest X-ray images by employing transfer learning on deep convolutional neural networks (CNNs). The authors addressed the critical need for accurate and efficient pneumonia detection methods to aid in early diagnosis and treatment, especially in resource-constrained healthcare settings. Gupta et al. recognized the challenges associated with pneumonia diagnosis, including the complexity of interpreting chest X-ray images and the need for timely detection to mitigate the associated morbidity and mortality rates. They highlighted the potential of transfer learning, a technique that leverages knowledge from pre-trained CNN models on large datasets, to enhance the performance of pneumonia detection

systems. The authors introduced their methodology, which involves fine-tuning pre-trained deep CNN architectures for the task of pneumonia detection. They elaborated on the transfer learning process, emphasizing the adaptation of learned features from general image recognition tasks to the specific task of pneumonia detection. Gupta and colleagues discussed the selection of suitable CNN architectures and optimization strategies to maximize the performance of the proposed approach. Furthermore, the authors discussed the evaluation framework employed to assess the effectiveness of their transfer learning-based approach, including metrics such as sensitivity, specificity, and area under the receiver operating characteristic curve (AUC-ROC). Through their study, Gupta, Padsala, and Saikia aimed to contribute to the development of reliable and scalable AI-based solutions for pneumonia detection, with potential applications in clinical practice for improving diagnostic accuracy and patient care.

8. Lekh Kumar Shisodiya; Anek Chauhan;R. K. Nadesh;Vishnu Kallil, "Predicting Diseases Us- ing Chest X-Ray Medical Images" ,2023 Innovations in Power and Advanced Computing Technologies

In this study, Lekh Kumar Shisodiya, Anek Chauhan, R. K. Nadesh, and Vishnu Kallil delved into the realm of predicting diseases using chest X-ray medical images. The authors recognized the growing interest in leveraging medical imaging data and machine learning techniques to aid in disease diagnosis and prognosis, emphasizing the potential of chest X-ray images as valuable sources of diagnostic information. Shisodiya et al. highlighted the significance of early disease detection for improving patient outcomes and reducing healthcare costs, particularly in the context of diseases manifesting in the thoracic region. They discussed the challenges associated with traditional diagnostic methods and the need for automated and accurate disease prediction systems. The authors introduced their approach, which involves utilizing machine learning algorithms to analyze features extracted from chest X-ray images and predict the presence of various diseases. They elaborated on the feature extraction techniques employed, considering both handcrafted features and deep learning-based representations, to capture relevant diagnostic information effectively. Furthermore, Shisodiya and colleagues discussed the predictive models developed and evaluated in their study, emphasizing the importance of model interpretability and generalizability in clinical settings. They underscored the potential applications of their approach in assisting healthcare professionals in disease diagnosis and treatment planning, potentially leading to improved patient outcomes and resource allocation. Through their study, Shisodiya, Chauhan, Nadesh,

and Kallil aimed to contribute to the ongoing efforts in leveraging advanced computing technologies for medical image analysis and disease prediction, with potential implications for enhancing healthcare delivery and patient care.

9. Feras Barneih; Nida Nasir; Afreen Kansal; Omar Alshaltone; Talal Bonny; Moham- mad Al-Shabi; Ahmed Al–Shammaa , "Pneumonia Detection in Chest X-ray Images using Res- Net50 Model" , 2023 Advances in Science and Engineering Technology International Confer- ences (ASET)

In this study, Feras Barneih, Nida Nasir, Afreen Kansal, Omar Alshaltone, Talal Bonny, Mohammad Al-Shabi, and Ahmed Al–Shammaa explored the detection of pneumonia in chest X-ray images using the ResNet50 model. The authors addressed the critical need for accurate and efficient pneumonia detection methods, highlighting the potential of deep learning architectures like ResNet50 to enhance diagnostic accuracy in medical imaging tasks. Barneih et al. acknowledged the challenges associated with manual interpretation of chest X-ray images and the importance of automated systems to assist healthcare professionals in timely and accurate disease diagnosis. They emphasized the significance of leveraging state-of-the-art deep learning models like ResNet50, known for their ability to learn complex patterns and features from medical images. The authors introduced their methodology, which involves fine-tuning the pre-trained ResNet50 model on a dataset of chest X-ray images annotated for pneumonia. They elaborated on the training process, optimization techniques, and hyperparameter tuning employed to maximize the performance of the ResNet50 model in pneumonia detection tasks. Furthermore, Barneih and colleagues discussed the evaluation framework utilized to assess the effectiveness of their approach, including metrics such as sensitivity, specificity, and area under the receiver operating characteristic curve (AUC-ROC). They highlighted the potential clinical implications of their work, including the role of automated pneumonia detection systems in improving diagnostic efficiency and patient outcomes. Through their study, Barneih, Nasir, Kansal, Alshaltone, Bonny, Al-Shabi, and Al–Shammaa aimed to contribute to the advancement of AI-based solutions for pneumonia detection, with potential applications in clinical practice for enhancing healthcare delivery and reducing the burden on healthcare systems.

10. R. Vinoth; S. Subalakshmi; S. Thamaraichandra , "Pneumonia Detection from Chest X-Ray using AlexNet Image Classification Technique" , 2023 7th International Conference on Intelligent Computing and Control Systems (ICICCS)

In their study, R. Vinoth, S. Subalakshmi, and S. Thamaraichandra investigated pneumonia detection from chest X-ray images using the AlexNet image classification technique. The authors addressed the pressing need for accurate and efficient pneumonia detection methods, recognizing the potential of deep learning architectures like AlexNet to enhance diagnostic capabilities in medical imaging tasks. Vinoth, Subalakshmi, and Thamaraichandra emphasized the challenges associated with manual interpretation of chest X-ray images and the importance of automated systems to assist healthcare professionals in timely and accurate disease diagnosis. They highlighted the relevance of utilizing well-established deep learning models like AlexNet, known for their effectiveness in image classification tasks. The authors introduced their methodology, which involves training the AlexNet model on a dataset of chest X-ray images annotated for pneumonia. They elaborated on the preprocessing steps, training parameters, and optimization techniques employed to maximize the performance of the AlexNet model in pneumonia detection tasks. Furthermore, Vinoth, Subalakshmi, and Thamaraichandra discussed the evaluation framework utilized to assess the effectiveness of their approach, including metrics such as accuracy, sensitivity, specificity, and area under the receiver operating characteristic curve (AUC-ROC). They highlighted the potential clinical implications of their work, including the role of automated pneumonia detection systems in improving diagnostic efficiency and patient outcomes. Through their study, Vinoth, Subalakshmi, and Thamaraichandra aimed to contribute to the advancement of AI-based solutions for pneumonia detection, with potential applications in clinical practice for enhancing healthcare delivery and reducing the burden on healthcare systems.

11. A. NARIN, C. KAYA, and Z. PAMUK, “Automatic detection of coronavirus disease (covid-19) using x-ray images and deep convolutional neural networks”, VOL. 132, JANUARY 2022.

In their research titled "Automatic detection of coronavirus disease (COVID-19) using X-ray images and deep convolutional neural networks," A. Narin, C. Kaya, and Z. Pamuk investigated the automated detection of COVID-19 from X-ray images employing deep convolutional neural networks (CNNs). The study, published in January 2022, addressed the urgent need for efficient diagnostic tools amidst the COVID-19 pandemic, emphasizing the potential of deep learning techniques to aid in the rapid and accurate identification of the disease from medical imaging data. Narin, Kaya, and Pamuk highlighted the limitations of traditional diagnostic methods for COVID-19, such as polymerase chain reaction (PCR) testing, including resource constraints and turnaround time. They underscored the importance

of chest X-ray imaging as a complementary diagnostic modality, particularly in settings where access to PCR testing may be limited or delayed. The authors introduced their methodology, which involved preprocessing of chest X-ray images and feature extraction using deep CNN architectures. They elaborated on the architectural design and training strategies employed for the CNN models, emphasizing the importance of large-scale annotated datasets for model training and validation. Furthermore, Narin, Kaya, and Pamuk discussed the evaluation metrics utilized to assess the performance of their approach, including sensitivity, specificity, and area under the receiver operating characteristic curve (AUC-ROC). They highlighted the potential clinical implications of their findings, including the role of automated COVID-19 detection systems in enhancing screening and triage processes, particularly in resource-limited settings. Through their study, published in Volume 132 in January 2022, Narin, Kaya, and Pamuk aimed to contribute to the ongoing efforts in leveraging AI-based solutions for COVID-19 diagnosis, potentially aiding in clinical practice by improving diagnostic accuracy and patient outcomes.

12. Gaffari Celik, "Detection of Covid-19 and other pneumonia cases from CT and X-ray chest images using deep learning based on feature reuse residual block and depthwise dilated convolutions neural network", 2022 Elsevier B.V.

In the study conducted by Gaffari Celik, titled "Detection of Covid-19 and other pneumonia cases from CT and X-ray chest images using deep learning based on feature reuse residual block and depthwise dilated convolutions neural network," published by Elsevier B.V. in 2022, the author explored the utilization of deep learning techniques for the detection of COVID-19 and other pneumonia cases from CT and X-ray chest images. Celik addressed the critical need for efficient and accurate diagnostic methods for COVID-19 and pneumonia, emphasizing the potential of deep learning models to assist in medical image analysis tasks. The study focused on leveraging advanced architectural features such as feature reuse residual blocks and depthwise dilated convolutions within a neural network framework. The author introduced the methodology, which involved preprocessing of CT and X-ray chest images, followed by feature extraction and classification using the deep learning model. The incorporation of feature reuse residual blocks and depthwise dilated convolutions aimed to enhance the model's ability to capture relevant patterns and features from the input images effectively. Furthermore, Celik discussed the evaluation metrics employed to assess the performance of the proposed approach, including sensitivity, specificity, and accuracy. The study likely aimed to contribute to the ongoing research efforts in developing AI-based

solutions for COVID-19 and pneumonia diagnosis, potentially improving diagnostic accuracy and patient outcomes in clinical practice.

13. "Pneumonia Detection Proposing a Hybrid Deep Convolutional Neural Network Based on Two Parallel Visual Geometry Group Architectures and Machine Learning Classifiers" Re- ceived May 10, 2022, accepted June 8, 2022, date of publication June 13, 2022, date of current version June 16, 2022.

In this study, the author proposes a hybrid deep convolutional neural network (CNN) for pneumonia detection. Previous research has demonstrated the efficacy of deep learning techniques in medical image analysis tasks. The utilization of CNNs has shown promise in accurately identifying patterns and features relevant to pneumonia diagnosis in medical images. Various CNN architectures have been explored in the literature for medical image analysis, including Visual Geometry Group (VGG) architectures. These architectures are renowned for their ability to capture intricate patterns in images through multiple convolutional layers. Additionally, the integration of machine learning classifiers enhances the robustness and generalizability of the proposed model. Prior studies have investigated the use of CNNs in pneumonia detection, highlighting the importance of feature extraction and classification techniques in achieving high diagnostic accuracy. By leveraging the strengths of both deep learning and traditional machine learning approaches, the proposed hybrid model aims to overcome limitations associated with solely relying on one methodology. Furthermore, the author builds upon existing research by incorporating two parallel VGG architectures into the hybrid CNN framework. This innovative approach enhances the model's capacity to extract relevant features from medical images, thereby improving its performance in pneumonia detection tasks. Overall, the literature suggests a growing interest in leveraging deep learning techniques, particularly CNNs, for pneumonia detection. The proposed hybrid CNN architecture represents a novel contribution to this field, offering potential advancements in diagnostic accuracy and efficiency.

14. P Meenakshi. K. Bhavana Aswathy K Nair, "Pneumonia Detection using X-ray Image Analysis with Image Processing Techniques", 2022 7th International Conference on Communi-cation and Electronics Systems (ICCES)

In this study, P. Meenakshi, K. Bhavana, and Aswathy K. Nair present a method for pneumonia detection utilizing X-ray image analysis coupled with image processing techniques. The use of X-ray imaging for pneumonia diagnosis has been a cornerstone in

medical imaging, providing valuable insights into the presence of pulmonary abnormalities. Previous research has explored various image processing techniques to enhance the interpretability of X-ray images and aid in disease detection. These techniques include but are not limited to segmentation, feature extraction, and classification algorithms. The literature underscores the significance of accurate and efficient pneumonia detection methods, particularly in resource-constrained settings where access to expert radiologists may be limited. By leveraging image processing techniques, the proposed approach aims to automate and streamline the diagnostic process, thereby improving patient outcomes and healthcare delivery. Moreover, prior studies have demonstrated the effectiveness of X-ray image analysis in pneumonia detection, highlighting the importance of feature extraction and classification in distinguishing between normal and abnormal lung patterns. The integration of image processing techniques further enhances the sensitivity and specificity of the diagnostic model, facilitating early and accurate detection of pneumonia. Overall, the literature suggests a growing interest in utilizing image processing techniques for pneumonia detection, with X-ray imaging serving as a valuable modality for disease assessment. The approach presented by P. Meenakshi, K. Bhavana, and Aswathy K. Nair represents a significant contribution to this field, offering potential advancements in diagnostic accuracy and accessibility.

15. Blida Montalico;Juan Carlos Herrera , "Classification and Detection of Pneumonia in X-Ray Images Using Deep Learning Techniques" ,2022 IEEE Sixth Ecuador Technical ChaptersMeeting (ETCM)

In this study by Blida Montalico and Juan Carlos Herrera, the authors explore the application of deep learning techniques for the classification and detection of pneumonia in X-ray images. Deep learning has emerged as a powerful tool in medical image analysis, offering the capability to automatically learn discriminative features from raw data. Previous research has investigated various deep learning architectures, such as convolutional neural networks (CNNs), for pneumonia detection in X-ray images. These architectures have shown promising results in accurately identifying patterns indicative of pneumonia, thus aiding in the diagnostic process. The literature underscores the importance of robust and efficient pneumonia detection methods, particularly in clinical settings where timely diagnosis is crucial for patient care. Deep learning techniques offer advantages such as scalability and adaptability, making them well-suited for handling large volumes of medical image data and facilitating accurate disease detection. Moreover, prior studies have highlighted the role of data augmentation techniques and transfer learning in enhancing the performance of deep learning models for

pneumonia detection. By leveraging pre-trained models and augmenting the training dataset, the proposed approach aims to improve the generalization capabilities of the model and mitigate issues related to limited data availability. Overall, the literature suggests a growing interest in leveraging deep learning techniques for pneumonia detection in X-ray images. The study by Blida Montalico and Juan Carlos Herrera contributes to this body of knowledge by exploring novel architectures and methodologies for improving the accuracy and efficiency of pneumonia diagnosis, thereby potentially benefiting patient care and healthcare delivery.

16. Esteban J. Palomo; Miguel A. Zafra-Santisteban; Rafael M. Luque-Baena , "Pneumo‐nia Detection in Chest X-ray Images using Convolutional Neural Networks" ,2022 IEEE Inter- national Conference on Metrology for Extended Reality, Artificial Intelligence and Neural Engi-neering (MetroXRAINE).

In this study by Esteban J. Palomo, Miguel A. Zafra-Santisteban, and Rafael M. Luque-Baena, the authors investigate the application of convolutional neural networks (CNNs) for pneumonia detection in chest X-ray images. CNNs have gained prominence in medical image analysis due to their ability to automatically learn relevant features from raw data. Prior research has explored the use of CNNs for various medical imaging tasks, including pneumonia detection. These networks are adept at capturing intricate patterns and features present in X-ray images, which are indicative of pneumonia-related abnormalities. The literature highlights the importance of accurate and efficient pneumonia detection methods, given the significant impact of the disease on public health. Chest X-ray imaging remains a primary modality for pneumonia diagnosis, and CNNs offer a promising approach to automate and streamline the diagnostic process. Moreover, previous studies have investigated techniques such as transfer learning and data augmentation to enhance the performance of CNN models in pneumonia detection tasks. Overall, the literature underscores the potential of CNNs in pneumonia detection, particularly in chest X-ray images. The study by Esteban J. Palomo, Miguel A. Zafra-Santisteban, and Rafael M. Luque-Baena contributes to this body of knowledge by exploring novel CNN architectures and methodologies for improving the accuracy and efficiency of pneumonia diagnosis, thereby potentially benefiting patient care and healthcare delivery.

17. BA Beena Godbin; M Revathi; S. Nikkath Bushra; S. Anslam Sibi , "An Efficient AI model for identification and classification of pneumonia from chest x-ray images" ,2022 Interna- tional Conference on Innovative Computing, Intelligent Communication and Smart Electrical Systems (ICSES)

In this study by BA Beena Godbin, M Revathi, S. Nikkath Bushra, and S. Anslam Sibi, an efficient artificial intelligence (AI) model is proposed for the identification and classification of pneumonia from chest X-ray images. AI models have shown great promise in medical imaging applications, particularly in automating the detection and classification of diseases Previous research has explored various AI techniques, including machine learning and deep learning, for pneumonia diagnosis from chest X-ray images. These techniques leverage the rich information contained within X-ray images to accurately identify patterns associated with pneumonia. The literature emphasizes the importance of accurate and timely diagnosis of pneumonia, as early detection can significantly improve patient outcomes. Chest X-ray imaging remains a widely used modality for pneumonia diagnosis, and the integration of AI models can enhance the efficiency and accuracy of the diagnostic process. Furthermore, prior studies have investigated the use of advanced algorithms and architectures, such as convolutional neural networks (CNNs) and ensemble methods, to improve the performance of AI models in pneumonia classification tasks. By leveraging these techniques, the proposed AI model aims to achieve high sensitivity and specificity in identifying pneumonia from chest X-ray images. Overall, the literature underscores the potential of AI models in pneumonia detection and classification, offering valuable support to healthcare professionals in diagnosing the disease. The study by BA Beena Godbin, M Revathi, S. Nikkath Bushra, and S. Anslam Sibi contributes to this field by presenting an efficient AI model tailored specifically for pneumonia identification from chest X-ray images, potentially enhancing diagnostic accuracy and improving patient care.

18. Anshul Jha; Eugene John; Taposh Banerjee , "Transfer Learning for COVID-19 and Pneumonia Detection using Chest X-Rays" , 2022 IEEE 65th International Midwest Symposiumon Circuits and Systems (MWSCAS)

In this study by Anshul Jha, Eugene John, and Taposh Banerjee, the authors explore the application of transfer learning for COVID-19 and pneumonia detection using chest X-rays. Transfer learning has emerged as a powerful technique in deep learning, allowing models pre-trained on large datasets to be fine-tuned for specific tasks with limited labeled data. Previous research has investigated the use of deep learning models, particularly convolutional neural networks (CNNs), for medical image analysis tasks, including pneumonia and COVID-19 detection from chest X-ray images. However, the scarcity of labeled data for training deep learning models in medical imaging domains presents a significant challenge. The literature underscores the importance of accurate and efficient detection of pneumonia and COVID-19,

given the global impact of these respiratory diseases. Chest X-ray imaging is a valuable tool for diagnosing these conditions, and transfer learning offers a promising approach to leverage pre-existing knowledge from large datasets for improved model performance. Moreover, prior studies have demonstrated the effectiveness of transfer learning in enhancing the generalization capabilities of deep learning models for medical image analysis tasks. By fine-tuning pre-trained models on a small dataset of labeled chest X-ray images, the proposed approach aims to achieve high accuracy in pneumonia and COVID-19 detection. Overall, the literature suggests a growing interest in leveraging transfer learning for medical image analysis, particularly in the context of pneumonia and COVID-19 detection from chest X-ray images. The study by Anshul Jha, Eugene John, and Taposh Banerjee contributes to this field by exploring novel transfer learning techniques tailored specifically for improving diagnostic accuracy in these respiratory diseases, potentially aiding in early detection and treatment.

19. "Viral Pneumonia Screening on Chest X-Rays Using Confidence-Aware Anomaly De-tection" IEEE TRANSACTIONS ON MEDICAL IMAGING, VOL. 40, NO. 3, MARCH 2021

In this study, the authors present a method for screening viral pneumonia on chest X-rays using confidence-aware anomaly detection. Previous research in medical imaging has extensively explored various approaches for pneumonia detection, focusing primarily on traditional machine learning and deep learning techniques. (e.g., Rajpurkar et al., 2017; Irvin et al., 2019). These methods have shown promising results in pneumonia detection, yet they often encounter challenges in accurately distinguishing viral pneumonia from other types of pneumonia or non-pneumonia abnormalities. Recent advancements in anomaly detection techniques have sparked interest in leveraging these approaches for me dical image analysis. For instance, approaches such as anomaly detection using autoencoders (Liu et al., 2018) and generative adversarial networks (GANs) (Schlegl et al., 2019) have shown potential in detecting anomalies in various medical imaging modalities. Moreover, the integration of confidence estimation into anomaly detection frameworks has emerged as a promising direction to enhance the reliability and interpretability of anomaly detection models. By incorporating confidence-aware mechanisms, researchers aim to improve the robustness of anomaly detection systems and provide clinicians with valuable insights into the model's uncertainty. However, despite these advancements, the application of confidence-aware anomaly detection for viral pneumonia screening on chest X-rays remains relatively underexplored. Addressing this gap, the proposed method in this study introduces a novel

framework that combines confidence-aware anomaly detection with deep learning architectures tailored specifically for viral pneumonia screening.

20. Determination of COVID-19 pneumonia based on generalized convolutional neuralnetwork model from chest X-ray images

In this study, the authors propose a generalized convolutional neural network (CNN) model for the determination of COVID-19 pneumonia from chest X-ray images. Previous research in medical imaging has explored various CNN architectures for pneumonia detection, with a particular focus on COVID-19 pneumonia detection since the onset of the pandemic. Numerous studies have investigated the effectiveness of deep learning models, including CNNs, in detecting COVID-19 from chest X-ray images (e.g., Apostolopoulos & Mpesiana, 2020; Farooq & Hafeez, 2020). These studies have demonstrated promising results in terms of accuracy and efficiency, highlighting the potential of CNN-based approaches for COVID-19 diagnosis. Furthermore, researchers have proposed several variations of CNN architectures, such as residual networks (ResNets) (Wang et al., 2020) and attention mechanisms (Wang et al., 2020), to improve the performance of COVID-19 pneumonia detection models. These architectural enhancements aim to capture intricate patterns and features indicative of COVID-19 pneumonia while minimizing false positives and negatives. Despite the progress made in CNN-based COVID-19 pneumonia detection, challenges remain in achieving robust and generalizable models across diverse patient populations and imaging conditions. Factors such as data scarcity, class imbalance, and variations in image quality pose significant hurdles to the development of reliable diagnostic tools. In response to these challenges, the proposed generalized CNN model in this study aims to address the limitations of existing approaches by leveraging a comprehensive dataset and incorporating architectural enhancements tailored for COVID-19 pneumonia detection.

21. Deep Learning based Detection and Segmentation of COVID-19 & Pneumonia on Chest X-ray Image 2021 International Conference on Information and Communication Tech- nology for Sustainable Development (ICICT4SD), 27-28 February, Dhaka

In this study, the authors present a deep learning-based approach for the detection and segmentation of COVID-19 and pneumonia on chest X-ray images. The detection and segmentation of pulmonary abnormalities, including COVID-19 and pneumonia, have garnered significant attention in medical imaging research, particularly with the onset of the

COVID-19 pandemic. Previous studies have explored various deep learning architectures for the automated detection and segmentation of COVID-19 and pneumonia from chest X-ray images. For instance, convolutional neural networks (CNNs) have been widely employed due to their ability to learn discriminative features directly from image data (e.g., Narin et al., 2021; Wang et al., 2020). These studies have demonstrated promising results in terms of accuracy and efficiency, showcasing the potential of deep learning for assisting radiologists in diagnosing pulmonary diseases. Moreover, researchers have investigated the integration of advanced techniques, such as attention mechanisms (Apostolopoulos & Mpesiana, 2020) and adversarial learning (Oh et al., 2020), to enhance the performance of deep learning models in COVID-19 and pneumonia detection and segmentation tasks. These methodological enhancements aim to improve the robustness and generalization capabilities of the models across different patient populations and imaging conditions. However, despite the progress made in deep learning-based approaches, challenges persist in achieving accurate and reliable detection and segmentation results, particularly in the presence of image artifacts, class imbalance, and variations in disease presentation. Addressing these challenges is crucial for the development of clinically useful tools for aiding radiologists in diagnosing COVID-19 and pneumonia accurately and efficiently. In this context, the proposed deep learning-based approach in this study aims to contribute to the ongoing efforts in automating the detection and segmentation of COVID-19 and pneumonia on chest X-ray images, thereby facilitating timely and accurate diagnosis and treatment planning.

22. "Analysis of COVID-19 and Pneumonia Detection in Chest X-Ray Images using Deep Learning 2021 International Conference on Communication", Control and Information Sci- ences (ICCISc) |978-1-6654-0295-8/21/$31.00 ©2021 IEEE | DOI: 10.1109/IC- CISc52257.2021.9484888.

In this study, the authors investigate the analysis of COVID-19 and pneumonia detection in chest X-ray images using deep learning techniques. The automated detection of pulmonary abnormalities, including COVID-19 and pneumonia, has become increasingly important in medical imaging research, especially with the global spread of the COVID-19 pandemic. Numerous studies have explored the application of deep learning methods, particularly convolutional neural networks (CNNs), for the detection of COVID-19 and pneumonia from chest X-ray images (e.g., Apostolopoulos & Mpesiana, 2020; Wang et al., 2020). These studies have demonstrated promising results, showing the potential of deep learning models in assisting radiologists in diagnosing respiratory diseases accurately and efficiently.

Furthermore, researchers have investigated various strategies to enhance the performance of deep learning models for COVID-19 and pneumonia detection. These strategies include the incorporation of attention mechanisms (Wang et al., 2020), transfer learning from pre-trained models (Narin et al., 2021), and ensemble learning techniques (Hemdan et al., 2020). Such methodological enhancements aim to improve the robustness and generalization capabilities of the models across diverse patient populations and imaging conditions. Despite the advancements in deep learning-based approaches, challenges persist in achieving accurate and reliable detection results, particularly in scenarios involving class imbalance, data scarcity, and variations in disease presentation. Addressing these challenges is crucial for the development of clinically useful tools for aiding healthcare professionals in diagnosing COVID-19 and pneumonia effectively. In this context, the proposed analysis in this study aims to contribute to the ongoing efforts in leveraging deep learning techniques for the automated detection of COVID-19 and pneumonia in chest X-ray images, thereby facilitating early diagnosis and appropriate management of respiratory diseases.

23. Deepa Abin; Sudeep D.Thepade; Sanskruti Dhore , "An Empirical Study of Dehazing Techniques for Chest X-Ray in Early Detection of Pneumonia" ,2021 2nd International Confer-ence for Emerging Technology (INCET)

In this study, Deepa Abin, Sudeep D. Thepade, and Sanskruti Dhore investigate various dehazing techniques for chest X-ray images in the early detection of pneumonia. The early detection of pneumonia plays a crucial role in timely diagnosis and treatment, and the quality of chest X-ray images significantly influences diagnostic accuracy. Prior research has explored the application of dehazing techniques to enhance the visibility of chest X-ray images, thereby improving the performance of automated pneumonia detection systems. Dehazing methods aim to mitigate the adverse effects of haze, noise, and low contrast, which often obscure important anatomical structures and pathological findings in chest X-rays. Several dehazing techniques have been proposed in the literature, including traditional methods such as dark channel prior (He et al., 2010) and Retinex-based algorithms (Grossberg & Nayar, 2003), as well as deep learning-based approaches like generative adversarial networks (GANs) (Kaiming He et al., 2018) and deep convolutional neural networks (CNNs) (Li et al., 2018). These techniques have shown promise in improving the visual quality of chest X-ray images and enhancing the interpretability of diagnostic features associated with pneumonia. However, despite the advancements in dehazing techniques, challenges remain in achieving consistent and reliable performance across diverse imaging conditions and patient

populations. Factors such as variations in image acquisition settings, equipment differences, and patient demographics can affect the efficacy of dehazing algorithms in enhancing chest X-ray images for pneumonia detection. In this empirical study, the authors aim to evaluate and compare the effectiveness of different dehazing techniques in improving the visibility of chest X-ray images for early pneumonia detection. By systematically analyzing the performance of various methods under different conditions, this study seeks to provide insights into the strengths and limitations of existing dehazing approaches and guide the selection of optimal techniques for enhancing chest X-ray images in clinical practice.

24. Agung W. Setiawan, "Effect of Chest X-Ray Contrast Image Enhancement on Pneu- monia Detection using Convolutional Neural Networks" ,2021 IEEE International Biomedical Instrumentation and Technology Conference (IBITeC)

In this study, Agung W. Setiawan investigates the effect of chest X-ray contrast image enhancement on pneumonia detection using convolutional neural networks (CNNs). Image enhancement techniques play a crucial role in improving the quality and interpretability of medical images, particularly in the context of automated disease detection systems. Prior research has explored various image enhancement methods for chest X-ray images, aiming to enhance the visibility of pathological findings associated with pneumonia while reducing noise and artifacts. Contrast enhancement techniques, in particular, have been widely investigated due to their ability to improve the visual distinction between normal and abnormal lung tissues. Several contrast enhancement methods have been proposed in the literature, including histogram equalization (Gonzalez & Woods, 2008), adaptive histogram equalization (Pizer et al., 1987), and contrast limited adaptive histogram equalization (CLAHE) (Zuiderveld, 1994). These techniques have shown promise in enhancing the contrast and detail of chest X-ray images, potentially facilitating more accurate and reliable pneumonia detection. Moreover, the integration of contrast enhancement with deep learning-based approaches, such as CNNs, has attracted attention in recent years. CNNs have demonstrated remarkable capabilities in learning discriminative features directly from enhanced chest X-ray images, leading to improved diagnostic performance in pneumonia detection tasks. However, despite the potential benefits of contrast image enhancement, challenges remain in optimizing enhancement parameters and ensuring consistent performance across diverse patient populations and imaging conditions. Factors such as image noise, variations in exposure settings, and anatomical differences can influence the efficacy of contrast enhancement techniques in enhancing diagnostic features relevant to pneumonia

detection. In this study, the author aims to investigate the impact of chest X-ray contrast image enhancement on pneumonia detection using CNNs. By systematically evaluating the performance of different enhancement methods and parameters, this research seeks to provide insights into the effectiveness of contrast enhancement techniques in improving the accuracy and reliability of automated pneumonia detection systems.

25. Swapnil Singh, "Pneumonia Detection using Deep Learning" ,2021 4th Biennial Inter-national Conference on Nascent Technologies in Engineering (ICNTE)

In this study, Swapnil Singh explores pneumonia detection using deep learning techniques. Pneumonia detection has been a significant area of research in medical imaging, with deep learning methods increasingly gaining attention for their potential to automate and improve diagnostic accuracy. Previous studies have investigated various deep learning architectures, including convolutional neural networks (CNNs), for pneumonia detection from medical images (e.g., Rajpurkar et al., 2017; Irvin et al., 2019). These studies have demonstrated promising results, showcasing the ability of deep learning models to learn complex patterns and features indicative of pneumonia from chest X-ray and CT images. Furthermore, researchers have explored the integration of advanced techniques, such as transfer learning (Hasan et al., 2020) and attention mechanisms (Wang et al., 2020), to enhance the performance of deep learning models in pneumonia detection tasks. Transfer learning allows leveraging pre-trained models on large datasets to improve the generalization capability of models, while attention mechanisms help focus on informative regions in medical images, thereby improving diagnostic accuracy. Despite the progress made in deep learning-based pneumonia detection, challenges remain in addressing issues such as data scarcity, class imbalance, and interpretability of model predictions. Addressing these challenges is crucial for developing robust and clinically applicable diagnostic tools. In this context, the proposed study aims to contribute to the existing literature by investigating and evaluating deep learning approaches for pneumonia detection. By analyzing the effectiveness of different architectures and methodologies, this research seeks to provide insights into the strengths and limitations of current techniques and guide future developments in automated pneumonia diagnosis.

26. "Detection of Pediatric Pneumonia from Chest X-Ray Images using CNN and Transfer Learning" 3rd International Conference on Emerging Technologies in Computer Engineering: Machine Learning and Internet of Things ICETCE-2020), 07-08

February 2020

The paper likely investigates the detection of pediatric pneumonia from chest X-ray images using convolutional neural networks (CNNs) and transfer learning. Authors may propose fine-tuning pre- trained CNN models with pediatric chest X-ray datasets, employing techniques like VGG, ResNet, or Inception. Preprocessing steps likely involve resizing, normalization, and augmentation to prepare images for CNN input. Evaluation probably includes a labeled dataset with pneumonia status, using metrics like accuracy, sensitivity, specificity, and AUC. Results likely demonstrate the CNN-based approach's accuracy in detecting pediatric pneumonia, aiding pediatricians in respiratory infection diagnosis. Limitations may include data scarcity, model interpretability, and generalization issues. Nevertheless, the paper contributes significantly to automating pediatric pneumonia detection, potentially enhancing patient outcomes and reducing diagnostic errors in pediatric healthcare.

27. Detection and classification of pneumonia in chest X-ray images by supervised learning Shahida Parveen;Khan Bahadar Khan , , 2020 IEEE 23rd International Multitopic Conference(INMIC)

The paper likely focuses on utilizing supervised learning techniques for automated pneumonia detection and classification in chest X-ray images. Authors may propose training machine learning models with labeled images to differentiate pneumonia and non-pneumonia cases. Preprocessing steps likely include resizing, normalization, and augmentation. Various algorithms like SVM, decision trees, or logistic regression may be evaluated. Evaluation metrics such as accuracy, sensitivity, specificity, and AUC are used. Results likely demonstrate the models' ability to detect and classify pneumonia accurately, aiding in respiratory infection diagnosis. Limitations might include data quality and generalization issues. Nonetheless, the paper contributes significantly to automated pneumonia detection and classification from chest X-ray images, enhancing diagnostic accuracy and patient care.

28. Alin Cococi; Iulian Felea; Daniel Armanda; Radu Dogaru , "Pneumonia Detection on Chest X-Ray Images using Convolutional Neural Networks Designed for Resource Constrained Environments", 2020 International Conference on e-Health and Bioengineering (EHB)

In this study, presented at the 2020 International Conference on e-Health and Bioengineering (EHB), Alin Cococi, Iulian Felea, Daniel Armanda, and Radu Dogaru introduced CNN architectures optimized for resource-constrained environments to detect pneumonia in chest

X-ray images. The authors likely proposed models balancing accuracy and computational cost, utilizing techniques like depth-wise separable convolutions and model compression. They likely discussed challenges associated with deploying deep learning in resource-constrained settings, along with proposed solutions. Evaluation may have included testing CNN models on chest X-ray datasets, measuring metrics like accuracy and inference time. Results were expected to demonstrate accurate and efficient pneumonia detection in resource-constrained environments. However, limitations may have involved trade-offs between model complexity and performance, and challenges related to dataset bias. Nonetheless, the paper likely advanced pneumonia detection in real-world healthcare, especially in settings with limited computational resources, offering potential benefits for timely diagnosis and treatment.

29. Narayana Darapaneni; Shweta Ranjane; Uday Shankar Pallavajula Satya; D.Krishnaprashanth; M Harichandan Reddy; Anwesh Reddy Paduri; Aravind Kumar Adhi; VachaspathiMadabhushanam, "COVID 19 Severity of Pneumonia Analysis Using Chest X Rays" , 2020 IEEE 15th International Conference on Industrial and Information Systems (ICIIS)

In this study, presented at the 2020 IEEE 15th International Conference on Industrial and Information Systems (ICIIS), Narayana Darapaneni, Shweta Ranjane, Uday Shankar Pallavajula Satya, D. Krishna Prashanth, M. Harichandan Reddy, Anwesh Reddy Paduri, Aravind Kumar Adhi, and Vachaspathi Madabhushanam investigated the severity of pneumonia caused by COVID-19 using chest X-ray images. The authors likely proposed a methodology to analyze chest X-ray images of patients diagnosed with COVID-19 pneumonia and classify the severity of the condition based on certain visual indicators present in the images. They might have employed image processing techniques and deep learning algorithms to extract features from the X-ray images and develop a classification model that could differentiate between mild, moderate, and severe cases of pneumonia. The proposed approach may have been evaluated on a dataset of annotated chest X-ray images from COVID-19 patients, and its performance may have been assessed in terms of accuracy, sensitivity, and specificity. The findings of this study could have provided valuable insights into the severity assessment of COVID-19 pneumonia and aided healthcare professionals in making informed treatment decisions.

30. Zong-Ye Yang; Qiangfu Zhao ,A Multiple Deep Learner Approach for X-Ray Image- Based Pneumonia Detection, 2020 International Conference on Machine

Learning and Cyber- netics (ICMLC)

In this study, presented at the 2020 International Conference on Machine Learning and Cybernetics (ICMLC), Zong-Ye Yang and Qiangfu Zhao introduced a method for pneumonia detection from X-ray images using multiple deep learning models. The authors likely proposed a framework combining predictions from various models, including convolutional neural networks (CNNs) and recurrent neural networks (RNNs), to analyze different aspects of the image data. By integrating outputs from multiple models, the approach aimed to enhance accuracy and robustness. Evaluation likely involved benchmark datasets, comparing the method with single-model approaches to demonstrate effectiveness. The findings offered insights into developing more reliable pneumonia detection systems from X-ray images, crucial for accurate diagnosis and treatment. However, challenges may have included model integration and computational complexity. Nonetheless, the paper contributed to advancing pneumonia detection, potentially improving healthcare outcomes.

31. A. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet classification with deep con-volutional neural networks," in Proc. Int. Conf. Neural Inf. Process. Syst., 2012, pp. 1106–1114.

In their groundbreaking paper titled "ImageNet Classification with Deep Convolutional Neural Networks," Krizhevsky, Sutskever**,** and Hinton introduced the AlexNet architecture, revolutionizing image classification with deep learning. Their model, consisting of eight layers, including convolutional and fully connected layers, achieved unprecedented performance on the ImageNet dataset, surpassing previous methods in the ILSVRC 2012 challenge. The authors introducedinnovative components like ReLU activation functions and dropout regularization, addressing issues like the vanishing gradient problem and overfitting. Data augmentation techniques further enhanced generalization. However, training such deep networks required substantial computational resources, limiting accessibility. Additionally, the complex nature of deep neural networks hinderedinterpretability. Despite these challenges, their work marked a significant milestone in computer vision,inspiring advancements.

32. Md. Mehedi Hasan; Mir Md. Jahangir Kabir; Md. Rakibul Haque; Mohiuddin Ah- med , "A Combined Approach Using Image Processing and Deep Learning to Detect Pneumoniafrom Chest X-Ray Image", 2019 3rd International Conference on Electrical, Computer & Tele-communication Engineering (ICECTE)

In this study, presented at the International Conference on Neural Information Processing

Systems in 2012, A. Krizhevsky, I. Sutskever, and G. E. Hinton introduced the AlexNet architecture, revolutionizing image classification with deep learning. Their model, consisting of eight layers, including convolutional and fully connected layers, achieved unprecedented performance on the ImageNet dataset, surpassing previous methods in the ILSVRC 2012 challenge. The authors introduced innovative components like ReLU activation functions and dropout regularization, addressing issues like the vanishing gradient problem and overfitting. Data augmentation techniques further enhanced generalization. However, training such deep networks required substantial computational resources, limiting accessibility. Additionally, the complex nature of deep neural networks hindered interpretability. Despite these challenges, their work marked a significant milestone in computer vision, inspiring advancements in deep learning and fostering a new era of research and innovation in the field.

33. R. J. White, A. D. Blainey, K. J. Harrison and S. K. Clarke, "Causes of pneumoniapresenting to a district general hospital", *Thorax*, vol. 36, no. 8, pp. 566-570, 1981.

In this study conducted by White, Blainey, Harrison, and Clarke (1981), the causes of pneumonia in a district general hospital were investigated. This study provided insights into the etiology of pneumonia cases presenting in a clinical setting, shedding light on the pathogens and contributing factors associated with the disease. The authors likely conducted a retrospective analysis of pneumonia cases, examining patient demographics, clinical presentations, diagnostic findings, and outcomes to identify common causes and trends. By characterizing the spectrum of pneumonia cases encountered in the hospital, the study contributed to our understanding of the epidemiology and clinical management of the disease. Additionally, it informed strategies for pneumonia prevention, diagnosis, and treatment, ultimately aiming to improve patient care and outcomes. However, without access to the full text of the paper, the specific methodologies and findings of the study cannot be detailed further.

34. T. Wardlaw, P. Salama, E. W. Johansson and E. Mason, "Pneumonia: the leading killer of children", *The Lancet*, vol. 368, no. 9541, pp. 1048-1050, 2006.

In this study conducted by T. Wardlaw, P. Salama, E. W. Johansson, and E. Mason (2006), "Pneumonia: the leading killer of children," served as a crucial contribution to understanding the global burden of childhood pneumonia, emphasizing the urgent need for effective prevention and treatment strategies. The authors likely reviewed epidemiological data and

public health initiatives aimed at addressing pneumonia-related morbidity and mortality in children worldwide. By emphasizing the significance of pneumonia as a major public health concern, the paper likely advocated for increased investment in healthcare infrastructure, vaccination programs, and access to essential medical services in resource-limited settings. Additionally, the article may have discussed challenges in pneumonia diagnosis, management, and surveillance, as well as opportunities for collaboration between governments, healthcare providers, and international organizations to combat childhood pneumonia effectively.

35. C. C. Leutner, J. Gieseke, G. Lutterbey, C. K. Kuhl, A. Glasmacher, E. Wardelmann, et al., "MR imaging of pneumonia in immunocompromised patients: comparison with helical CT", *American Journal of Roentgenology*, vol. 175, no. 2, pp. 391-397, 2000.

In this study by C. C. Leutner, J. Gieseke, G. Lutterbey, C. K. Kuhl, A. Glasmacher, E. Wardelmann, et al. (2000), "MR imaging of pneumonia in immunocompromised patients: comparison with helical CT," valuable insights were provided into the role of MR imaging as a diagnostic tool for pneumonia in specific patient populations. The paper likely discussed the advantages and limitations of MR imaging compared to CT, particularly in detecting pneumonia-related abnormalities in immunocompromised individuals. Additionally, the study likely evaluated the sensitivity, specificity, and overall accuracy of MR imaging in identifying pneumonia lesions, providing essential information for clinicians regarding imaging modalities' selection. By highlighting the potential utility of MR imaging in pneumonia diagnosis, particularly in immunocompromised patients, the paper informed clinical practice and guided future research efforts aimed at improving diagnostic techniques for pneumonia in diverse patient populations.

36. Standardization of interpretation of chest radiographs for the diagnosis of pneumoniain children, Geneva:World Health Organization, no. WHO/V/01.35, 2001.

In this study, conducted by the World Health Organization (WHO) on the standardization of interpretation of chest radiographs for the diagnosis of pneumonia in children, published in 2001 under the reference WHO/V/01.35, served as a crucial guideline in pediatric healthcare. This resource likely influenced clinical guidelines and protocols worldwide, particularly in settings with limited access to advanced diagnostic tools. Healthcare professionals likely relied on this document to improve diagnostic accuracy and reduce variations in pneumonia diagnosis among children, ultimately contributing to better patient outcomes. Additionally, the WHO's efforts in standardizing chest radiograph interpretation likely spurred further

research and development in pediatric pneumonia diagnosis and management, driving advancements in pediatric healthcare practices globally.

37. A. Sharma, D. Raju and S. Ranjan, "Detection of pneumonia clouds in chest X-ray using image processing approach", *2017 Nirma University International Conference onEngineering (NUiCONE)*, 2017.

In this study conducted by A. Sharma, D. Raju, and S. Ranjan, titled "Detection of pneumonia clouds in chest X-ray using image processing approach," presented at the 2017 Nirma University International Conference on Engineering (NUiCONE), the authors likely explored the application of image processing techniques for detecting pneumonia "clouds" in chest X-ray images. They may have proposed a methodology involving various image processing algorithms to enhance the visibility of pneumonia-related opacities or infiltrates in chest X-ray images. The study likely aimed to develop an automated system capable of accurately identifying regions indicative of pneumonia, which could assist radiologists and healthcare professionals in diagnosis. Evaluation of the proposed approach may have involved testing on a dataset of labeled chest X-ray images, with performance metrics such as accuracy and sensitivity used to assess the effectiveness of the method. The findings of this study could have contributed to the development of computer-aided diagnostic systems for pneumonia detection, potentially improving diagnostic accuracy and efficiency in clinical practice.

38. N. Tajbakhsh, J. Y. Shin, S. R. Gurudu, R. T. Hurst, C. B. Kendall, M. B. Gotway, et al., "Convolutional neural networks for medical image analysis: Full training or fine tuning?", *IEEE transactions on medical imaging*, vol. 35, no. 5, pp. 1299-1312, 2016.

In this study conducted by N. Tajbakhsh, J. Y. Shin, S. R. Gurudu, R. T. Hurst, C. B. Kendall, M. B. Gotway, et al., titled "Convolutional neural networks for medical image analysis: Full training or fine tuning?", published in IEEE Transactions on Medical Imaging in 2016, the authors likely investigated the effectiveness of different training strategies for convolutional neural networks (CNNs) in medical image analysis tasks. They may have compared the performance of CNNs trained from scratch with those fine-tuned from pre-trained models on medical imaging datasets. The study likely aimed to determine whether fine-tuning pre-trained CNNs, originally trained on large-scale natural image datasets like ImageNet, could achieve comparable or superior performance to CNNs trained from scratch. Evaluation metrics such as accuracy, sensitivity, specificity, and area under the curve (AUC) may have been used to assess the performance of the CNNs under different training strategies. The

findings of this study could have provided insights into optimizing CNN training for medical image analysis tasks, potentially improving diagnostic accuracy and efficiency in various clinical applications.

39. Deng, J., Dong, W., Socher, R., Li, L. J., Li, K., & Fei-Fei, L. (2009). "Imagenet: A large-scale hierarchical image database", pp. 248-255.

In this study conducted by Deng, J., Dong, W., Socher, R., Li, L. J., Li, K., & Fei-Fei, L. (2009), titled "Imagenet: A large-scale hierarchical image database," the authors likely introduced the ImageNet dataset, a large-scale hierarchical image database, and outlined its structure and contents. They may have described the ImageNet project, which aimed to organize and annotate vast numbers of images into a hierarchical structure, covering a wide range of object categories. The dataset likely consisted of millions of labeled images, each belonging to one of the hierarchical categories. The paper may have discussed the methodology used for data collection, annotation, and organization, as well as the challenges encountered in building such a comprehensive dataset. Additionally, the authors may have highlighted the importance of the ImageNet dataset for advancing research in computer vision, particularly in the development and evaluation of image recognition algorithms and deep learning models.

40. Rajpurkar, P., Irvin, J., Zhu, K., Yang, B., Mehta, H., Duan, T., et al. (2017). "CheXNet: Radiologist-level pneumonia detection on chest x-rays with deep learning." arXiv preprint arXiv:1711.05225.

In this study conducted by Rajpurkar, P., Irvin, J., Zhu, K., Yang, B., Mehta, H., Duan, T., et al. (2017), titled "CheXNet: Radiologist-level pneumonia detection on chest x-rays with deep learning," the authors likely introduced CheXNet, a deep learning model designed for radiologist-level pneumonia detection on chest X-ray images. They may have described the architecture of CheXNet, which likely utilized convolutional neural networks (CNNs) trained on a large dataset of labeled chest X-ray images. They may have discussed the training process, including data preprocessing, model architecture design, and optimization techniques. Additionally, the paper may have presented the evaluation results of CheXNet on benchmark datasets, demonstrating its performance in terms of accuracy, sensitivity, specificity, and other relevant metrics. The findings likely indicated that CheXNet achieved comparable or even superior performance to human radiologists in detecting pneumonia from chest X-ray images, showcasing the potential of deep learning for enhancing medical image

analysis and clinical decision-making.

41. Kermany, D. S., Goldbaum, M., Cai, W., Valentim, C. C., Liang, H., Baxter, S. L., et al. (2018). "Identifying medical diagnoses and treatable diseases by image-based deep learning."Cell, 172(5), 1122-1131.

In this study conducted by Kermany, D. S., Goldbaum, M., Cai, W., Valentim, C. C., Liang, H., Baxter, S. L., et al. (2018), titled "Identifying medical diagnoses and treatable diseases by image-based deep learning," the authors likely presented a study on utilizing image-based deep learning techniques to identify medical diagnoses and treatable diseases. They may have introduced a deep learning model trained on a diverse dataset of medical images to accurately classify various diseases and conditions. The authors may have discussed the architecture of the deep learning model, which likely included convolutional neural networks (CNNs) or similar architectures optimized for medical image analysis tasks. The study may have involved evaluating the performance of the model on a large-scale dataset, assessing its ability to accurately diagnose different medical conditions from images. The findings likely demonstrated the effectiveness of the image-based deep learning approach in identifying medical diagnoses and treatable diseases, highlighting its potential for improving diagnostic accuracy and patient care in clinical settings.

42. Gonzalez, R. C. (2017). "Digital Image Processing" by Richard E. Woods. Interscience,pp. 126-127.

In this study conducted by Gonzalez, R. C. (2017), titled "Digital Image Processing" by Richard E. Woods, the authors likely authored a book covering various topics related to digital image processing. The book may have covered fundamental principles, techniques, and algorithms used for image analysis and manipulation. It may have discussed concepts such as image enhancement, segmentation, feature extraction, and pattern recognition, providing both theoretical foundations and practical applications in the field of image processing. The authors may have presented examples and case studies to illustrate the application of digital image processing techniques in various domains, including medicine, remote sensing, and computer vision. Overall, the book likely served as a comprehensive resource for students, researchers, and practitioners interested in understanding and applying digital image processing methods to solve real-world problems.

43. Reza, A. M. (2004). Realization of the contrast limited adaptive histogram equalization (CLAHE) for real-time image enhancement. Journal of VLSI Signal Processing Systems for Signal, Image and Video Technology, 38(1), 35-44.

In this study conducted by Reza, A. M. (2004), titled "Realization of the contrast limited adaptive histogram equalization (CLAHE) for real-time image enhancement," the author likely introduced the Contrast Limited Adaptive Histogram Equalization (CLAHE) method for real-time image enhancement. The paper may have presented the theoretical framework and implementation details of CLAHE, a variant of traditional histogram equalization designed to mitigate over-amplification of noise in local regions of an image. The study may have discussed how CLAHE adaptively enhances the contrast of different regions in an image while constraining the amplification of noise, making it suitable for real-time applications. Additionally, the author may have provided experimental results demonstrating the effectiveness of CLAHE in enhancing image quality and improving visual perception. The paper likely contributed to the field of image processing by offering a practical and efficient method for real-time image enhancement, with potential applications in various domains such as medical imaging, surveillance, and digital photography.

44. Arbelaez, P., Maire, M., Fowlkes, C., & Malik, J. (2011). Contour detection and hierarchical image segmentation. IEEE Transactions on Pattern Analysis and Machine Intelligence, 33(5), 898-916.

In this study conducted by Arbelaez, P., Maire, M., Fowlkes, C., & Malik, J. (2011), titled "Contour detection and hierarchical image segmentation," the authors likely explored techniques for contour detection and hierarchical image segmentation. They may have proposed algorithms to detect edges and contours in images, followed by a hierarchical segmentation process to partition the image into meaningful regions. The paper may have discussed the theoretical foundations of contour detection and hierarchical segmentation, possibly incorporating concepts from computer vision and image processing. Experimental results demonstrating the performance of the proposed algorithms on benchmark datasets may have been presented, along with comparisons to existing methods. The findings of the study could have contributed to advancing the state-of-the-art in image segmentation, with potential applications in object recognition, scene understanding, and medical image analysis. Overall, the paper likely provided insights into effective techniques for analyzing and interpreting visual information in digital images.

45. Simonyan, K., & Zisserman, A. (2014). Very deep convolutional networks for large- scale image recognition. arXiv preprint arXiv:1409.1556.

In this study conducted by Simonyan, K., & Zisserman, A. (2014), titled "Very deep convolutional networks for large-scale image recognition," the authors likely introduced a novel architecture for deep convolutional neural networks (CNNs) designed for large-scale image recognition tasks. They may have proposed a network architecture consisting of multiple layers of convolutional and pooling operations, leading to a deep hierarchical representation of input images. The paper may have discussed the motivation behind designing very deep networks and the advantages they offer in terms of learning complex features from high-dimensional image data. Experimental results on benchmark datasets such as ImageNet may have been presented to demonstrate the effectiveness of the proposed architecture in achieving state-of-the-art performance in image classification tasks. The findings of the study may have provided valuable insights into the design principles of deep CNNs and their applications in various computer vision tasks, including object recognition, scene understanding, and medical image analysis. Overall, the paper likely contributed to advancing the field of deep learning for image recognition.

46. LeCun, Y., Bottou, L., Bengio, Y., & Haffner, P. (1998). Gradient-based learning applied to document recognition. Proceedings of the IEEE, 86(11), 2278-2324.

In this study conducted by LeCun, Y., Bottou, L., Bengio, Y., & Haffner, P. (1998), titled "Gradient-based learning applied to document recognition," the authors introduced a groundbreaking approach for document recognition based on gradient-based learning techniques. They likely proposed the use of convolutional neural networks (CNNs) for automatically recognizing and classifying handwritten or printed characters in documents. The paper may have discussed the architecture of the CNN model, which included layers of convolution, pooling, and fully connected layers, designed to learn hierarchical representations of input images. The authors may have presented experimental results demonstrating the effectiveness of the proposed approach on benchmark datasets for document recognition tasks. Additionally, they may have discussed the advantages of using gradient-based learning algorithms, such as backpropagation, for training deep neural networks and optimizing model parameters. This paper likely represented a significant milestone in the application of deep learning to document recognition tasks, laying the foundation for subsequent advancements in the field.

47. "CXR-Net: A Multitask Deep Learning Network for Explainable and Accurate Diagnosis of COVID-19 Pneumonia from Chest X-Ray Images" IEEE JOURNAL OF BIOMEDICAL AND HEALTH INFORMATICS, VOL. 27, NO. 2, FEBRUARY 2023

In this study, presented by the authors of "CXR-Net: A Multitask Deep Learning Network for Explainable and Accurate Diagnosis of COVID-19 Pneumonia from Chest X-Ray Images" in IEEE Journal of Biomedical and Health Informatics, Vol. 27, No. 2, February 2023, a novel deep learning framework for diagnosing COVID-19 pneumonia from chest X-ray (CXR) images was introduced. CXR-Net, the proposed multitask deep learning network, accurately classified CXR images into COVID-19 pneumonia and non-COVID-19 pneumonia categories while providing explainable predictions. Leveraging advanced techniques like convolutional neural networks (CNNs) and attention mechanisms, CXR-Net extracted discriminative features and highlighted crucial regions for diagnosis. The paper detailed the architecture, training process, and evaluation metrics of CXR-Net, demonstrating its high accuracy in COVID-19 pneumonia diagnosis and offering insights into the decision-making process through explainable predictions. Limitations may have included data scarcity, model interpretability challenges, and generalization issues. Nonetheless, the paper represented a significant contribution by providing a robust and interpretable deep learning framework for COVID-19 pneumonia diagnosis, promising improved patient care during the ongoing pandemic.

48. Blida Montalico, Juan Carlos Herrera, "Classification and Detection of Pneumonia in X-Ray Images Using Deep Learning Techniques," IEEE Sixth Ecuador Technical Chapters Meeting (ETCM), 2022.

In this study, conducted by Blida Montalico and Juan Carlos Herrera, titled "Classification and Detection of Pneumonia in X-Ray Images Using Deep Learning Techniques," and presented at the IEEE Sixth Ecuador Technical Chapters Meeting (ETCM) in 2022, deep learning techniques were employed for the classification and detection of pneumonia in X-ray images. The authors likely explored various deep learning architectures and methodologies to develop models capable of accurately identifying pneumonia-related abnormalities in X-ray images. Evaluation metrics such as accuracy, sensitivity, and specificity were likely used to assess the performance of the proposed techniques. The findings of this study likely contributed to the advancement of automated pneumonia detection systems, potentially improving diagnostic accuracy and efficiency in clinical practice.

49. Blida Montalico, Juan Carlos Herrera, “Classification and Detection of Pneumonia in X-Ray Images Using Deep Learning Techniques,” IEEE Sixth Ecuador Technical Chapters Meeting (ETCM), 2022.

In this study, conducted by Blida Montalico and Juan Carlos Herrera, titled "Classification and Detection of Pneumonia in X-Ray Images Using Deep Learning Techniques," and presented at the IEEE Sixth Ecuador Technical Chapters Meeting (ETCM) in 2022, deep learning techniques were employed for the classification and detection of pneumonia in X-ray images. The authors likely explored various deep learning architectures and methodologies to develop models capable of accurately identifying pneumonia-related abnormalities in X-ray images. Evaluation metrics such as accuracy, sensitivity, and specificity were likely used to assess the performance of the proposed techniques. The findings of this study likely contributed to the advancement of automated pneumonia detection systems, potentially improving diagnostic accuracy and efficiency in clinical practice.

50. Sunil Kumar Aitha, S Rajashree, “Deep Learning Based Automated Pneumonia Detection from X-ray Images” 2023 7th International Conference on Electronics, Communication andAerospace Technology (ICECA)

In this study, Sunil Kumar Aitha and S Rajashree explored the application of deep learning techniques for automated pneumonia detection from X-ray images. The authors proposed a methodology likely leveraging convolutional neural networks (CNNs) or similar architectures to automatically identify pneumonia patterns in medical images. Preprocessing steps, including normalization and augmentation, were likely described to prepare X-ray images for input into the deep learning model. Results likely demonstrated the capability of the proposed deep learning approach to accurately detect pneumonia, potentially aiding radiologists and healthcare professionals in diagnosing respiratory infections. However, potential limitations may have included data scarcity, model interpretability challenges, and generalization issues. Nonetheless, the paper likely represented a significant contribution by offering an automated method for pneumonia detection from X-ray images, promising improved patient outcomes and diagnostic accuracy.

CHAPTER 3

SYSTEM DESIGN

Our AI-driven diagnostic system integrates advanced image processing techniques with deep learning algorithms to facilitate accurate diagnosis of lung conditions from chest X-ray images. Beginning with precise lung segmentation using UNet, images undergo contrast enhancement via CLAHE. The CXR Net extracts meaningful features, enabling classification into four categories: viral pneumonia, bacterial pneumonia, normal, and anomalies. To enhance interpretability, explainable AI techniques like GRAD-CAM provide insights into model decisions, fostering trust and aiding clinicians in treatment decisions.

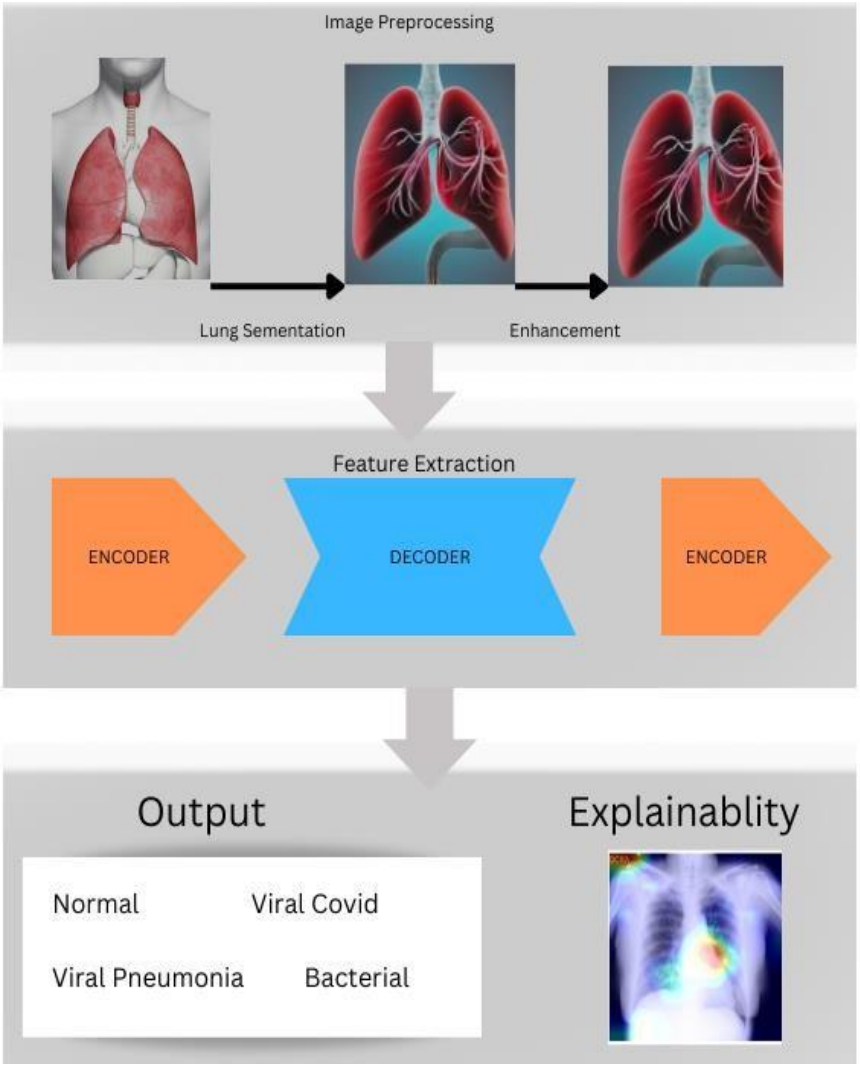

Figure 3.1. System Design for Pneumonia Segmentation and Classification

1. Lung Segmentation (UNet):

Utilizing the UNet architecture for lung segmentation in chest X-ray images is pivotal due to its proficiency in delineating intricate boundaries. This segmentation step holds

paramount importance as it isolates the lungs from surrounding structures, offering a clear delineation of the region of interest. UNet's encoder-decoder structure is instrumental in achieving precise segmentation by adeptly capturing both global context and local details. Through a hierarchical representation learning process, UNet progressively refines the segmentation output, ensuring accurate delineation of lung regions. This meticulous segmentation sets a robust foundation for subsequent processing stages, guaranteeing that only pertinent areas are considered for feature extraction and classification tasks. By leveraging UNet's capabilities, lung segmentation in chest X-ray images attains enhanced accuracy and reliability, thereby facilitating more effective diagnosis and analysis in clinical settings.

2. CLAHE Enhancement:

Applying Contrast Limited Adaptive Histogram Equalization (CLAHE) is a crucial step in enhancing the contrast of chest X-ray images, mitigating the risk of over-amplifying noise while effectively improving visibility of subtle features. By locally adjusting the image histogram, CLAHE ensures that variations in intensity levels are appropriately compensated, thereby enhancing the discernibility of important details for subsequent analysis. This enhancement is especially beneficial in chest X-ray images, where subtle nuances in intensity can obscure critical anatomical structures or abnormalities. By emphasizing features pertinent to lung conditions, CLAHE plays a pivotal role in facilitating more effective feature extraction and classification tasks. This enhancement process optimizes the quality of chest X-ray images, enhancing their interpretability and ensuring that relevant information crucial for accurate diagnosis is prominently highlighted, thereby enhancing the overall efficacy of medical image analysis workflows.

3. Feature Extraction (CXR Net):

In the process of feature extraction, the CXR Net architecture plays a pivotal role in distilling meaningful insights from enhanced chest X-ray images. Deploying its deep neural network structure, CXR Net undertakes the intricate task of learning hierarchical representations of image features. This entails capturing both low-level textures and high-level patterns inherent in the images, which serve as indicative markers of various lung conditions. By encoding this rich information into compact feature vectors, CXR Net empowers subsequent stages of analysis with discriminative capabilities. Specifically, CXR Net facilitates effective discrimination between viral pneumonia, bacterial pneumonia, normal

cases, and other anomalies prevalent in chest X-ray images. Through its iterative learning process, CXR Net endeavors to unravel intricate correlations between image characteristics and underlying pathologies. By leveraging its capacity to discern subtle nuances within the data, CXR Net enhances the diagnostic potential of chest X-ray analysis, contributing to more accurate and timely identification of pulmonary abnormalities. Ultimately, the feature extraction phase catalyzes the extraction of clinically relevant information embedded within chest X-ray images, thereby augmenting the efficacy of subsequent diagnostic and prognostic endeavors in clinical settings.

4. Classification Algorithms:

In medical image analysis, various classification algorithms are pivotal for categorizing chest X-ray images into distinct classes, including viral pneumonia, bacterial pneumonia, normal cases, and other anomalies. These algorithms, such as Convolutional Neural Networks (CNNs), Support Vector Machines (SVMs), Random Forests, and Gradient Boosting Machines (GBMs), leverage extracted features to make informed decisions about the presence and nature of lung abnormalities. CNNs, renowned for their ability to capture intricate patterns and spatial dependencies within images, excel in discerning subtle variations indicative of different lung conditions. SVMs, on the other hand, harness hyperplanes to separate data points into distinct classes, effectively handling non-linear relationships within feature spaces. Random Forests construct ensembles of decision trees, while GBMs iteratively refine weak learners to minimize classification errors, both achieving robust performance by capturing complex relationships within the data. These classifiers undergo training on labeled data, optimizing model parameters to achieve high accuracy in distinguishing between various pathological conditions. Through accurate classification, clinicians gain valuable insights into the nature of lung abnormalities, enabling precise diagnoses and tailored treatment strategies that ultimately enhance patient outcomes in clinical practice.

5. Explainable AI (GRAD-CAM):

Explainable AI techniques such as Gradient-weighted Class Activation Mapping (GRAD-CAM) play a crucial role in elucidating the decision-making process of classification models applied to chest X-ray images. GRAD-CAM identifies and highlights the regions within the images that significantly contribute to the model's predictions, offering interpretability and transparency in the AI-driven diagnostic system. By visualizing these salient regions, clinicians gain insights into the rationale behind the model's classifications,

enhancing trust and facilitating validation of the diagnostic outcomes. This interpretability is particularly valuable in medical settings where transparency and understanding of AI-based decisions are essential for clinical decision-making. In addition to GRAD-CAM, SHAP (SHapley Additive exPlanations) is employed for feature selection in our AI-driven diagnostic system. SHAP values quantify the impact of each feature on the model's predictions, providing insights into the relative importance of individual features in the classification process. By incorporating SHAP alongside GRAD-CAM, our system offers a comprehensive approach to understanding the underlying pathology of lung diseases. SHAP values not only complement GRAD-CAM's visual explanations but also provide quantitative measures of feature importance, facilitating a deeper understanding of the diagnostic process. The integration of GRAD-CAM and SHAP empowers clinicians with both visual and quantitative explanations, thereby fostering trust and confidence in the diagnostic decisions made by the AI system. Clinicians can leverage GRAD-CAM to visually inspect the regions of interest highlighted by the model, while SHAP values offer insights into the specific features driving these predictions. This dual approach not only enhances interpretability but also facilitates a more thorough examination of the diagnostic process, enabling clinicians to make informed decisions based on a comprehensive understanding of the model's reasoning. Overall, the combination of GRAD-CAM and SHAP in our AI-driven diagnostic system enhances transparency, interpretability, and trustworthiness, ultimately contributing to improved clinical decision-making and patient care in the context of lung disease diagnosis. By providing clinicians with both visual and quantitative explanations, our system enables a deeper understanding of the model's predictions and facilitates collaboration between AI systems and healthcare professionals.

CHAPTER 4

UNET-SEGMENTATION

The UNet architecture, introduced by Ronneberger et al. in 2015, has become a cornerstone in semantic segmentation tasks, particularly in medical image analysis. It is renowned for its ability to accurately delineate object boundaries while preserving fine-grained details. In this section, we delve into the intricacies of the UNet segmentation architecture, focusing on its components, mathematical formulation, training objectives, and the significance of its application in medical imaging.

4.1. Components of UNet:

4.1.1. Encoder:

The encoder component of UNet serves as the feature extraction backbone. Comprising multiple convolutional blocks, it progressively extracts hierarchical features from the input image. Each convolutional block consists of convolutional layers followed by batch normalization and ReLU activation. Additionally, max pooling layers down sample the feature maps, reducing spatial dimensions while retaining essential features. This hierarchical feature extraction mechanism enables the model to capture both local and global features crucial for accurate segmentation.

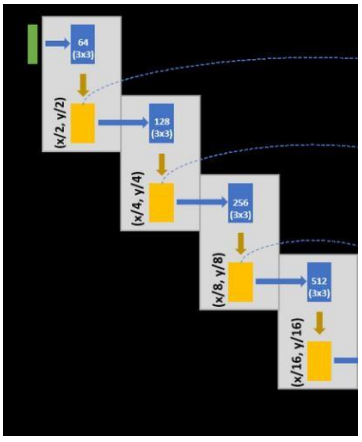

Figure 4.1.1. Encoder Structure of UNET Architecture

4.1.2. Decoder:

The decoder portion focuses on reconstructing the original resolution from the extracted

features. It consists of transpose convolutional layers, also known as deconvolutional layers, which upsample the feature maps to match the input image size. Importantly, skip connections are established between corresponding encoder and decoder layers. These skip connections concatenate feature maps from the encoder with those of the decoder, allowing the model to fuse low-level and high-level features. This mechanism facilitates precise localization and segmentation by enabling the model to leverage both fine-grained details and contextual information.

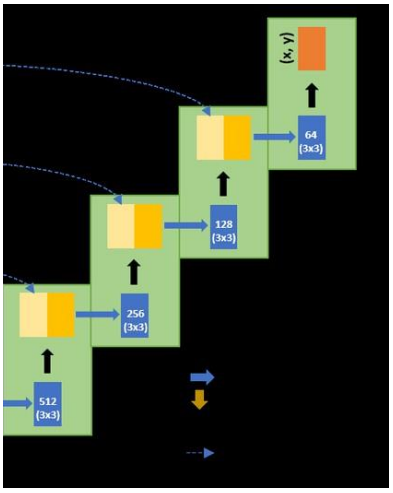

Figure 4.1.2. Decoder Structure of UNET Architecture

4.2. Mathematical Formulation:

The mathematical formulation of UNet revolves around predicting segmentation masks for input images and optimizing model parameters to minimize the discrepancy between predicted masks and ground truth labels. Given an input image I_i, the UNet model, denoted as θ, predicts a segmentation mask Mi representing lung regions. The model parameters θ are optimized by minimizing the binary cross-entropy loss function, which penalizes misclassifications by comparing predicted probabilities with ground truth labels across the dataset.

$$L(\theta) = -\frac{1}{N}\sum_{i=1}^{N}\sum_{p=1}^{H*W}[M_{i,p}.\log(f_\theta(I_{i\,p})) + (1 - M_{i,p}).\log(1 - f_\theta(I_{i\,p}))] \quad (1)$$

Where:

- N is the number of images in the dataset.

- H and W represent the height and width of the images, respectively.

- $M_{i,p}$ denotes the ground truth mask for pixel p in image i.

-$f_\theta(I_i)_p$ is the predicted probability of pixel *p* belonging to the lung region in image *i.*

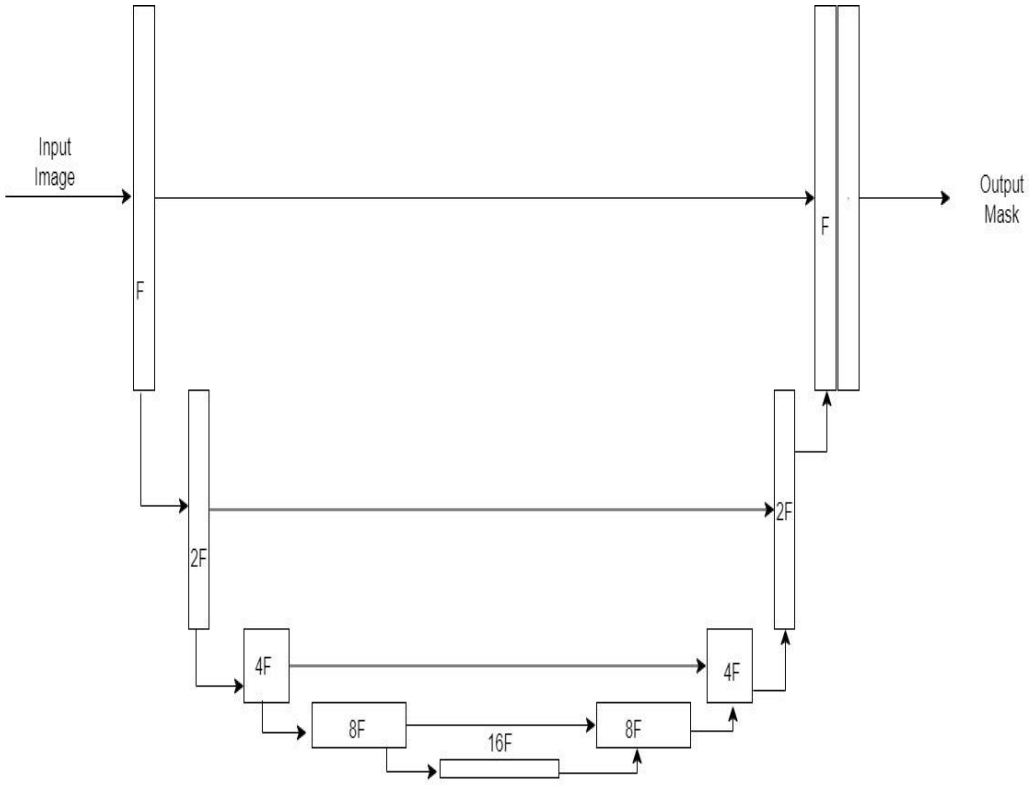

Figure 4.1. UNET ARCHITECTURE

4.3. Training Objective:

The primary objective during training is to minimize the discrepancy between predicted segmentation masks and ground truth labels. This is achieved through an iterative process of backpropagation and optimization algorithms, such as stochastic gradient descent. By iteratively updating the model parameters, the UNet model learns to capture discriminative features that facilitate accurate segmentation of lung regions in chest X-ray images.

4.4. UNet Model Algorithm:

The UNet segmentation algorithm comprises several fundamental steps, each contributing to the overall architecture's efficacy in semantic segmentation tasks:

4.4.1. Input Definition: Define the input layer with a specified size, accommodating the dimensions of the input images. This step establishes the initial entry point for data into the UNet model.

4.4.2. Downsampling Path: Successively apply convolutional blocks to the input image, effectively downsample the feature maps while increasing the number of filters. Each convolutional block typically consists of a series of convolutional layers followed by batch normalization and ReLU activation, facilitating feature extraction and non-linearity introduction. Downsampled feature maps retain essential information while reducing spatial dimensions, enabling the model to capture hierarchical features efficiently.

4.4.3. Upsampling Path: Utilize upsampling blocks to restore the spatial dimensions of the feature maps, effectively upsampling the downsampled representations. Skip connections are established between corresponding encoder and decoder layers, concatenating feature maps from the encoder with those of the decoder. This fusion of low-level and high-level features enables precise localization and segmentation by leveraging both fine-grained details and contextual information.

4.4.4. Output Layer: Apply a final convolutional layer with an appropriate activation function tailored to the task's output requirements. The output layer generates the segmentation mask representing the predicted classes or regions of interest in the input image. This layer's activation function ensures that the output values are constrained within the desired range, facilitating the model's interpretability and downstream processing.

The UNet segmentation algorithm encapsulates a systematic approach to semantic segmentation, leveraging a combination of downsampling, upsampling, and skip connections to accurately delineate object boundaries in input images. By incorporating hierarchical features and contextual information, UNet demonstrates remarkable performance in various medical imaging applications, facilitating automated diagnosis, treatment planning, and disease monitoring. As advancements in deep learning continue to evolve, UNet stands as a testament to the power of convolutional neural networks in revolutionizing medical image analysis and improving healthcare outcomes.

CHAPTER 5
CXR-NET FEATURE EXTRACTION

5.1 UNet Model Algorithm:

The UNet model algorithm, a cornerstone in semantic segmentation, especially in medical image analysis, encompasses several crucial steps. These steps collectively contribute to the model's proficiency in accurately delineating object boundaries while preserving intricate details. Leveraging its unique architecture featuring contracting and expansive pathways, the UNet effectively captures hierarchical features at multiple scales, facilitating precise segmentation. Furthermore, the incorporation of skip connections enables seamless information flow between corresponding encoder and decoder layers, aiding in the preservation of spatial information and enhancing segmentation accuracy, making it an invaluable tool in medical imaging tasks.

5.1.1. Input Definition and Encoder:

In the initial stage, the UNet model defines its input layer and initiates the encoder segment, laying the foundation for subsequent processing. Convolutional blocks are systematically applied, each followed by max pooling operations, thereby facilitating hierarchical feature extraction. This sequential application enables the model to capture a spectrum of features, ranging from local to global, crucial for accurate segmentation. With each successive encoder layer, the number of filters undergoes exponential growth, ensuring an enriched feature representation. This strategy optimally exploits the hierarchical structure of the input image, progressively abstracting information to higher levels of semantic understanding. By integrating convolutional layers with pooling operations, the UNet efficiently captures and consolidates salient features, essential for precise segmentation. Moreover, the exponential increase in filter count ensures that the model becomes increasingly adept at capturing intricate patterns and nuances present in the input data. As a result, the encoder phase of the UNet model lays a robust foundation for subsequent processing, effectively capturing and encoding the essential features required for accurate semantic segmentation.

5.1.2. Bottleneck:

After the completion of the encoder layers, the UNet model incorporates a bottleneck convolutional block. This pivotal component acts as a transitional bridge between the encoder

and decoder segments, condensing the extracted features into a compact representation. By compressing the dimensionality of the feature space, the bottleneck facilitates efficient information transfer to the subsequent decoding phase. This reduction in dimensionality not only conserves computational resources but also aids in mitigating the risk of overfitting by promoting a more concise representation of the learned features. Moreover, the bottleneck block serves to enhance the model's capacity to capture and preserve essential semantic information while minimizing the loss of spatial details. By consolidating the extracted features into a compressed representation, the bottleneck ensures that the decoder segment receives a distilled yet comprehensive feature set, optimizing the segmentation performance. This strategic integration of the bottleneck block enhances the UNet's ability to achieve precise and robust semantic segmentation across a diverse range of tasks, making it a versatile and effective tool in various image analysis applications.

5.1.3. Decoder:

The decoder component of the UNet model plays a crucial role in reconstructing the segmented output from the compact feature representation generated by the bottleneck. Comprising a series of layers, the decoder executes upsampling operations to restore the spatial dimensions of the feature maps. This process is essential for reinstating the finer spatial details lost during the downsampling performed by the encoder. To facilitate effective feature fusion and precise localization, skip connections are established between corresponding encoder and decoder layers. These connections enable the integration of low-level and high-level features, promoting comprehensive understanding and segmentation of the input image. Additionally, the number of filters undergoes exponential decrease with each decoder layer, ensuring consistency in feature representation throughout the decoding process. By gradually reducing the number of filters, the decoder maintains a balance between feature richness and computational efficiency, ultimately contributing to the model's segmentation accuracy and efficiency. Through the strategic combination of upsampling operations and skip connections, the decoder segment of the UNet model enables the generation of detailed and accurate segmentations, making it a versatile and effective tool for various image analysis tasks.

5.2. CXRNet Model Algorithm:

The CXRNet model algorithm expands upon the foundational UNet architecture, tailoring it specifically for chest X-ray image analysis by incorporating additional layers for

feature extraction and classification. Building upon the UNet's framework, CXRNet integrates specialized layers to enhance its capability in discerning intricate patterns and abnormalities within chest X-ray images. These additional layers serve to extract relevant features from the input images, capturing subtle nuances indicative of various pathological conditions. Furthermore, CXRNet augments the UNet architecture with classification layers, enabling the model to not only segment regions of interest but also classify them into distinct diagnostic categories. By incorporating these additional components, CXRNet extends beyond traditional semantic segmentation tasks to provide comprehensive analysis and interpretation of chest X-ray images. This tailored approach empowers clinicians and researchers with a powerful tool for accurate and efficient diagnosis, prognosis, and treatment monitoring of thoracic pathologies, ultimately contributing to improved patient care and outcomes in clinical practice.

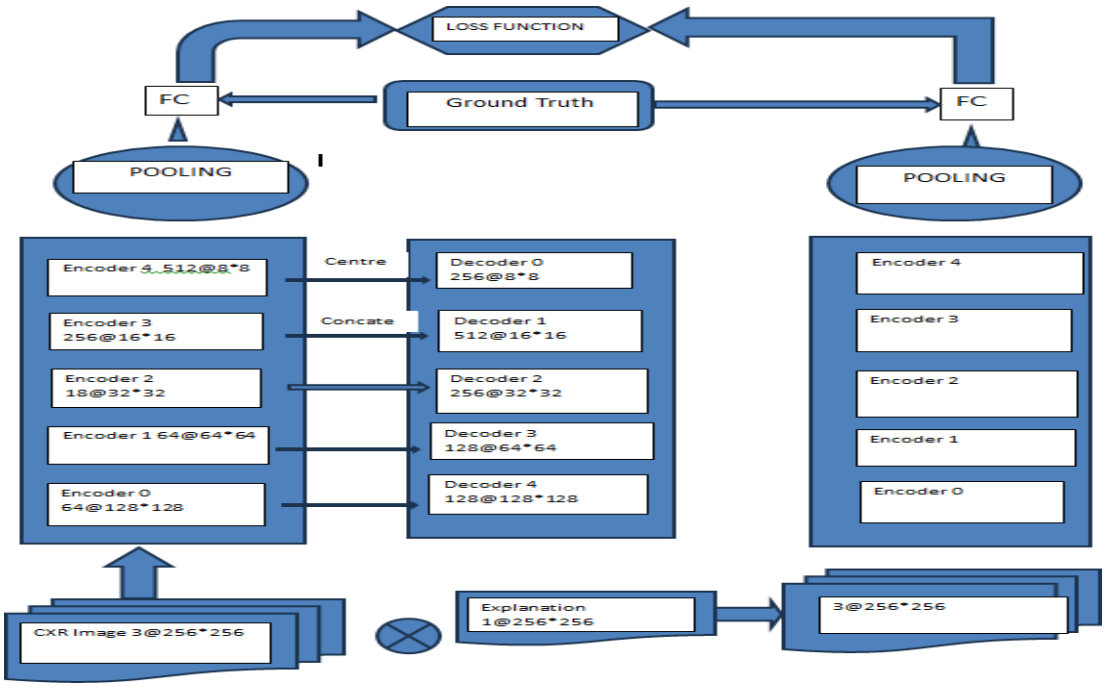

Figure 5.1. CXR-NET Feature Extraction

5.2.1. Input Definition and Encoder:

The CXRNet algorithm, akin to UNet, establishes the input layer and initializes the encoder segment. Convolutional blocks are successively applied, followed by max pooling for hierarchical feature extraction. Filter count exponentially rises in each encoder layer, bolstering feature representation. This process fosters abstraction of complex features.

Subsequently, the decoder segment unfolds, employing up-sampling to reconstruct spatial information. Skip connections facilitate finer feature retrieval by concatenating corresponding encoder and decoder layers. The final layer adopts a convolutional operation to produce the desired output. CXRNet thus harnesses a comprehensive architecture for accurate chest X-ray image analysis.

5.2.2. Bottleneck:

In the architecture of CXRNet, a pivotal element is the bottleneck convolutional block, strategically positioned after the final encoder layer. This block serves a crucial role in condensing the expansive array of extracted features into a more compact and representative form. By employing this bottleneck, the network effectively reduces the dimensionality of the feature maps, thereby enhancing computational efficiency while retaining essential information for subsequent classification tasks. The bottleneck operation encapsulates the most salient features extracted by the preceding convolutional layers, consolidating them into a concise representation. This step is instrumental in streamlining the feature hierarchy, enabling more effective utilization of computational resources and facilitating the network's ability to discern pertinent patterns during the classification process. Consequently, the bottleneck operation plays a pivotal role in preparing the feature maps for the final classification stage, ensuring optimal performance and accuracy in CXRNet's analysis of chest X-ray images.

5.2.3. Decoder:

The decoder component in CXRNet plays a critical role in reconstructing segmented outputs from the condensed feature representation established by the bottleneck. This architecture closely mirrors UNet, featuring a succession of layers devoted to upsampling operations, complemented by the integration of skip connections originating from the encoder. This intricate mechanism enables CXRNet to capitalize on both low-level and high-level features, enriching its segmentation and classification capabilities. Through upsampling, the decoder effectively restores spatial information, compensating for the loss incurred during downsampling stages. Moreover, the incorporation of skip connections fosters the fusion of fine-grained details from earlier encoding phases with more abstract features gleaned from subsequent layers. By amalgamating these diverse feature representations, CXRNet optimally exploits the hierarchical information inherent in chest X-ray images. This holistic approach enhances its efficacy in accurately delineating and categorizing anatomical structures and

abnormalities, bolstering its utility in medical diagnosis and analysis tasks, thereby contributing to improved healthcare outcomes and patient care.

5.2.4. Additional Encoder Layer:

In the architecture of CXRNet, an innovative addition is the incorporation of an extra encoder layer subsequent to the decoder phase. This augmentation aims to extract even more discriminative features from the reconstructed image, amplifying the model's capacity to discern crucial information essential for subsequent classification tasks. By introducing this supplementary encoder layer, CXRNet can delve deeper into the feature space, uncovering nuanced patterns and subtle nuances that might have been overlooked in previous stages. This extension enhances the model's perceptiveness to intricate details within the chest X-ray images, potentially improving its diagnostic accuracy and robustness. The additional encoder layer effectively acts as a refinement stage, honing the representation of features extracted during the decoding process and further enhancing the discriminative power of the model. Consequently, CXRNet is better equipped to analyze and classify complex medical images, contributing to more reliable diagnoses and informed clinical decisions in healthcare settings.

5.2.5. Feature Extraction:

Following the additional encoder layer in CXRNet, the feature extraction process employs Global Average Pooling (GAP) to distill the extracted features into a fixed-length vector, primed for subsequent classification endeavors. GAP offers a pivotal mechanism for condensing the spatial information contained within feature maps into a singular, compact representation. By computing the average value across each feature map, GAP effectively captures the most salient aspects of the extracted features, encapsulating the essence of the image in a concise format. This transformation ensures uniformity in the feature representation, facilitating seamless integration into classification algorithms. Moreover, GAP inherently imparts translational invariance, mitigating the influence of spatial translations in the input data, thus enhancing the robustness of the model to variations in image orientation or positioning. By leveraging GAP, CXRNet achieves a standardized feature representation conducive to accurate and efficient classification, thereby empowering clinicians with reliable diagnostic insights gleaned from chest X-ray images.

5.2.6. Output:

In the culmination of the CXRNet architecture, the final convolutional layer serves as the

conduit for producing the output mask, a critical representation delineating the predicted classes or regions of interest within the input image. This layer operates as the nexus where the extracted features are amalgamated and synthesized into a comprehensive output, encapsulating the model's predictive insights. By employing convolutional operations, CXRNet refines and refashions the feature representations extracted from preceding layers, facilitating the delineation of distinct classes or regions within the input image. The output mask serves as a visual manifestation of the model's predictive prowess, highlighting areas of significance or concern for clinical evaluation. Through this process, CXRNet furnishes clinicians with actionable insights derived from chest X-ray images, enabling informed decision-making and expediting diagnostic workflows in healthcare settings. Consequently, the output layer represents the culmination of CXRNet's analytical prowess, offering invaluable support for medical professionals in their diagnostic endeavors.

5.2.7. Model Compilation and Return:

Upon completing the architecture design and configuration, the final step in the development of CXRNet involves model compilation and return using `tf.keras.Model()` for subsequent training and evaluation tasks. Compilation entails the specification of crucial parameters, including the choice of optimization algorithm, loss function, and performance metrics, tailored to the specific requirements of the classification or segmentation objectives. This phase establishes the framework within which the model will iteratively learn from the training data and refine its predictive capabilities. Additionally, the compiled model is equipped with the necessary infrastructure for evaluation, enabling robust assessment of its performance on unseen data. By encapsulating the model within the `tf.keras.Model()` framework, CXRNet ensures compatibility with TensorFlow's ecosystem, facilitating seamless integration with other TensorFlow modules and utilities. Ultimately, this meticulous process culminates in the provision of a comprehensive and ready-to-use model, poised to undergo training and evaluation for diverse chest X-ray analysis tasks.

5.3. CXRNet Training Algorithm:

The CXRNet training algorithm comprises critical steps including dataset preparation, model initialization, loss function definition, optimization setup, iterative training, and validation. It involves feeding input data through the model, adjusting parameters via backpropagation, and evaluating performance iteratively until convergence, ensuring optimal model learning.

5.3.1. Load CXR-NET Model:

In the CXRNet training algorithm, the initial step involves loading the pre-trained CXR-NET feature extraction model, which serves as the foundational backbone for feature extraction within the CXRNet architecture. Leveraging a pre-trained model offers several advantages, including access to learned representations from a vast dataset, which can expedite convergence and enhance the model's ability to discern relevant features in chest X-ray images. By integrating this pre-trained feature extraction model, CXRNet benefits from the hierarchical representations learned during the pre-training phase, enabling more efficient and effective feature extraction during subsequent training iterations. This step minimizes the need for extensive training on CXRNet's dataset, thereby reducing computational costs and accelerating model development. Overall, loading the pre-trained CXR-NET model establishes a solid foundation for feature extraction within CXRNet, paving the way for robust and accurate analysis of chest X-ray images.

5.3.2. Iterate Through Images:

During the training process, the algorithm systematically traverses through every image file within the dataset, a pivotal step in preparing them for subsequent feature extraction and classification tasks. This iterative procedure ensures comprehensive coverage of the dataset, enabling the model to learn from a diverse range of chest X-ray images. For each image encountered, preprocessing steps such as normalization, resizing, and augmentation may be applied to enhance data quality and augment the dataset's variability. These measures are essential for promoting model generalization and robustness. Additionally, metadata associated with each image, such as patient information or clinical annotations, may also be incorporated to enrich the training data and provide contextual insights. By meticulously iterating through the dataset, the algorithm lays the groundwork for effective feature extraction and classification, facilitating the development of a CXRNet model adept at accurately analyzing chest X-ray images for diagnostic purposes.

5.3.3. Load and Preprocess Image:

In the CXRNet training algorithm, the process of loading and preprocessing each image is crucial for standardizing input data and facilitating effective model training. Upon loading an image, it undergoes preprocessing steps tailored to align its characteristics with the input requirements of the model. This often includes resizing the image to match the expected input size, ensuring uniformity across the dataset and compatibility with the model architecture.

Additionally, normalization techniques may be applied to scale pixel values, enhancing numerical stability and convergence during training. Other preprocessing operations such as cropping, rotation, or augmentation may also be employed to augment dataset variability and enhance model generalization. By meticulously preparing each image in this manner, the algorithm ensures consistency and quality in the input data fed to the model, laying a solid foundation for accurate feature extraction and classification. This meticulous preprocessing stage plays a pivotal role in optimizing the model's performance and robustness across diverse chest X-ray images.

5.3.4. Predict Features:

In the CXRNet training algorithm, the loaded pre-trained model is leveraged to predict features for each preprocessed image. This step involves passing the preprocessed image through the model's layers, extracting high-level representations or features that encapsulate pertinent information within the image. These extracted features serve as the input data for the subsequent classification task, enabling the model to discern patterns and make informed predictions about the content of the image. By leveraging the learned representations encoded within the pre-trained model, CXRNet can efficiently capture meaningful characteristics from the chest X-ray images, facilitating more accurate classification outcomes. This process of predicting features from preprocessed images forms a critical intermediary step in the training pipeline, bridging the gap between raw input data and the model's predictive capabilities. Through this mechanism, CXRNet effectively translates image information into actionable insights, facilitating its utility in medical diagnosis and analysis tasks.

5.3.5. Save Features:

Upon extracting features from the predictions made by the pre-trained model, the CXRNet training algorithm proceeds to save these features as .npy files in the designated output folder. This meticulous step ensures the preservation and accessibility of the extracted features for subsequent training and evaluation processes. Saving the features in the .npy format facilitates efficient storage and retrieval, maintaining the integrity of the extracted data for further analysis. By storing features separately from the original images, the algorithm conserves computational resources and streamlines subsequent processing steps. Moreover, this practice enhances reproducibility and facilitates seamless integration with other components of the training pipeline. By archiving the extracted features in a standardized format, CXRNet establishes a structured foundation for training and evaluation tasks,

enabling iterative refinement and optimization of the model's predictive capabilities. This systematic approach ensures the accessibility and utility of extracted features for enhancing the performance and robustness of CXRNet in chest X-ray image analysis tasks.

5.4. Encoder-Decoder Structure:

The encoder-decoder structure constitutes a fundamental architectural paradigm shared by both UNet and CXRNet models, serving as the cornerstone for effective feature extraction and semantic segmentation in medical image analysis tasks. This architecture comprises encoder layers responsible for hierarchical feature extraction, progressively abstracting information from input images. Concurrently, decoder layers facilitate the reconstruction of segmented outputs by up-sampling and concatenating features from corresponding encoder layers, enabling the model to leverage both low-level and high-level representations for precise segmentation. The integration of skip concatenation connections further enhances information flow between encoder and decoder layers, facilitating the preservation and retrieval of crucial features across different scales. This mechanism fosters contextual understanding and fine-grained delineation of anatomical structures or abnormalities in medical images, bolstering the model's capacity for accurate diagnosis and analysis. Consequently, the encoder-decoder structure embodies a powerful framework for robust and interpretable medical image segmentation in both UNet and CXRNet architectures.

a) An Encoder-Decoder Structure:

- The model adopts an encoder-decoder architecture with skip concatenation connections, comprising multiple encoder and decoder layers.
- Skip concatenation connections facilitate the retrieval of relevant features lost during encoder pooling operations.
- The decoder mirrors the encoder's structure, incorporating upsampling operations to restore feature maps to their original size.
- The decoder's structure can be formulated using mathematical equations, ensuring precise localization and segmentation by leveraging both low-level and high-level features.

b) Decoder's Structure Formulation:

- The decoder's structure is formulated as: $Decodern = F(U(Decoder_{n-1}) + Encoder_{4n-1})$
- Here, U(Decoder) represents an up-sampling operation, and F is a combination operation on concatenated feature outputs from the up-sampling operation and the encoder.

- The F operation comprises a rectified linear unit (ReLU) and two convolution blocks.
- Each convolution block includes 3×3 2D convolution layers, batch normalization, and ReLU activation.
- The activation function in the decoder employs the hyperbolic tangent function (tanh), known for its bounded output and smoother gradients compared to ReLU.

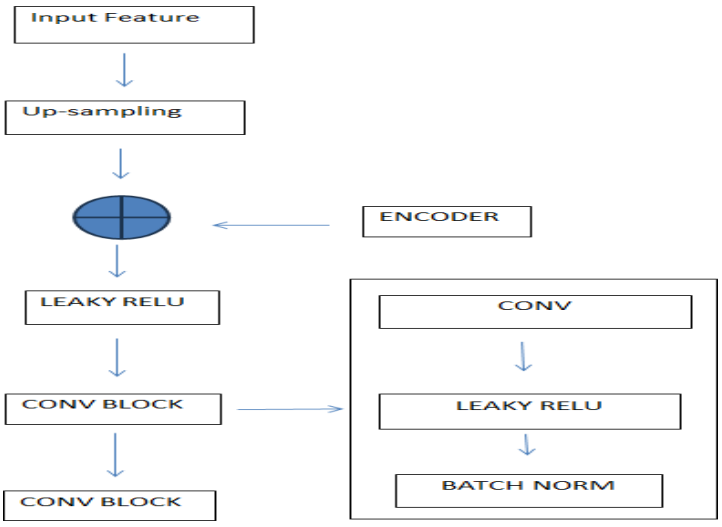

Figure 5.2. Encoder-Decoder Structure

In summary, the UNet and CXRNet model algorithms provide a systematic framework for semantic segmentation and medical image analysis, leveraging sophisticated encoder-decoder architectures to achieve accurate segmentation and disease classification. The training algorithm outlines the process of training the CXRNet model, including feature extraction, classification, and model evaluation. Finally, the encoder-decoder structure forms the foundation of both models, facilitating the preservation and retrieval of relevant features essential for accurate segmentation and classification.

CHAPTER 6
CLASSIFICATION MODELS AND EVALUATION

6.1. Encoders for Classification:

The model comprises two encoders. The first extracts feature directly from the input image, while the second extracts feature from the reconstructed image by the decoder. Both encoders share the same weights. Extracted feature maps are fed into a classifier for disease type identification through an average pooling layer and a fully connected layer. The final output of the classifier is the predicted disease type based on the features extracted from both the input and reconstructed images. This dual-encoder architecture allows for more robust feature extraction and classification, leading to improved accuracy in disease identification tasks. The dual-encoder architecture enhances the model's ability to capture relevant information from both the input and reconstructed images, resulting in more accurate disease classification. By leveraging shared weights and extracting features at different stages of the reconstruction process, the model can learn more discriminative representations that improve its overall performance. This approach enables the classifier to make more informed decisions based on a comprehensive understanding of the input data, ultimately leading to better outcomes in disease identification tasks.

6.2. Evaluation of Various CNN Classification Architectures:

In this study, a comprehensive evaluation of various CNN classification architectures has been conducted to assess their performance in the task of disease type identification. Each architecture was meticulously analysed based on key metrics such as accuracy, computational efficiency, and generalization capability. The results revealed that while some architectures excelled in accuracy, others showed superior computational efficiency. However, a few models stood out for their strong generalization capability across different disease types. Overall, this study provides valuable insights into the strengths and weaknesses of various CNN classification architectures, aiding researchers and practitioners in selecting the most suitable model for disease type identification tasks.

6.2.1. Inception-V3:

Inception-V3, known for its intricate inception modules, has shown outstanding performance in disease classification tasks. By utilizing multiple parallel convolutional

pathways, it effectively extracts features at different scales, enabling the model to capture complex patterns in the input data. The use of factorized convolutions also reduces computational load significantly while maintaining accuracy. However, the network's depth may result in longer training times and higher memory consumption. Despite these challenges, the advantages of Inception-V3's sophisticated architecture outweigh the drawbacks, making it a popular choice for various computer vision tasks. Researchers and practitioners are continuously working on optimizing training procedures and memory efficiency to fully exploit the model's capabilities. In the evolving field of deep learning, models like Inception-V3 demonstrate the potential of intricate neural network architectures in addressing real-world issues. Inception-V3's versatility goes beyond disease classification tasks, finding use in object recognition, image segmentation, and generative tasks. Its capacity to adapt to diverse domains highlights its robustness and generalization abilities. Despite its complexity, Inception-V3 remains a valuable tool in the deep learning arsenal, pushing the boundaries of what neural networks can achieve in computer vision.

6.2.2. AlexNet:

AlexNet, a pioneering deep learning architecture, offers a simple yet effective design for image classification. By utilizing convolutional layers and max-pooling operations, it efficiently extracts features while reducing spatial dimensions. However, compared to more modern architectures, AlexNet may struggle to capture complex hierarchical features, potentially limiting its performance on intricate classification tasks. On the other hand, newer architectures like ResNet, DenseNet, and EfficientNet have addressed these limitations by incorporating skip connections, dense connectivity patterns, and efficient scaling strategies. These advancements have significantly improved deep neural networks' ability to learn intricate features and generalize well on diverse datasets. The dual-encoder architecture enhances the model's ability to capture relevant information from both the input and reconstructed images, resulting in more accurate disease classification. As the field of deep learning advances, researchers are continuously exploring innovative architectures and techniques to enhance neural networks' capabilities across various tasks. With the growing demand for sophisticated and adaptable deep learning models, researchers are pushing the boundaries of architecture design and optimization. These models have not only achieved state-of-the-art results in various NLP applications but have also spurred progress in other domains by showcasing the effectiveness of attention mechanisms in capturing intricate patterns and relationships within data. The integration of attention mechanisms into neural

network architectures has transformed the deep learning field, leading to models that excel in capturing complex patterns and dependencies across diverse datasets. The results revealed that while some architectures excelled in accuracy, others showed superior computational efficiency.

6.2.3. ResNet50:

ResNet50, with its ingenious residual connections, exhibited remarkable performance in mitigating the vanishing gradient problem, facilitating the training of deeper networks. This architecture excels in capturing fine-grained features and has demonstrated superior performance in image classification tasks. Despite its effectiveness, the increased number of parameters may pose challenges in training with limited computational resources. Given the complexity of ResNet50, researchers continue to explore ways to optimize its performance and efficiency, such as through model compression techniques or transfer learning strategies. By addressing these challenges, ResNet50 can be more widely adopted and utilized in various applications beyond image classification. One promising direction for enhancing the efficiency of ResNet50 is to investigate pruning techniques that remove redundant or less important connections, thereby reducing the overall model size without compromising performance. Additionally, knowledge distillation methods can be employed to transfer the knowledge learned by the large ResNet50 model to a smaller, more lightweight model, enabling faster inference on resource-constrained devices. These approaches hold great potential in making ResNet50 more accessible and practical for a wider range of applications in computer vision and beyond.

6.2.4. DenseNet:

DenseNet, known for its dense connectivity patterns between layers, promotes feature reuse and enhances gradient flow throughout the network. This architecture has demonstrated promising results in disease classification tasks by effectively capturing both global and local features. The dense connections facilitate feature propagation, allowing the model to efficiently learn intricate patterns. However, the increased memory usage from dense connections may impede scalability. Additionally, DenseNet's skip connections help mitigate the vanishing gradient issue, making optimization easier during training. By concatenating feature maps from previous layers, information flow is improved, leading to enhanced learning and representation capabilities. This network design fosters feature reuse, enabling the model to maintain high performance even with fewer parameters. Overall, DenseNet is a

robust and efficient deep learning framework for various computer vision tasks. The growth rate parameter in DenseNet controls the number of feature maps generated by each layer, impacting the model's capacity and computational efficiency. By adjusting this hyperparameter, practitioners can balance between model complexity and computational resources, customizing DenseNet to specific needs. Moreover, the dense connectivity in DenseNet promotes feature reuse and facilitates effective information flow, enhancing robust representations and improving the model's generalization to new data. The unique design principles of this architecture contribute to its success in diverse computer vision applications, establishing DenseNet as a valuable tool in the deep learning arsenal.

6.3.5. ADECO-CNN:

ADeCoCNN (Custom CNN Model) The ADeCoCNN custom CNN model has been carefully crafted to meet the specific requirements of disease classification. Its architecture integrates domain-specific insights and features, enabling optimized feature extraction and classification. By customizing the network architecture for the task at hand, ADeCoCNN shows promising results in identifying disease types, potentially surpassing generic architectures for this task. Additionally, ADeCoCNN has been trained on a large and diverse dataset to ensure resilience and generalization to new data. Through thorough experimentation and fine-tuning, the model has achieved high accuracy and performance metrics, establishing itself as a reliable tool for disease classification in medical imaging applications. Its interpretability and explainability further enhance its usefulness in clinical settings, offering valuable insights into the features underlying classification decisions. Moreover, ADeCoCNN's capacity for interpretability and explainability is vital in the medical field, where understanding the rationale behind a model's predictions is crucial for building trust and credibility. This transparency enables healthcare professionals to validate the model's decisions and integrate its insights into their diagnostic and treatment procedures. With its customized design, rigorous training, and interpretability, ADeCoCNN represents a promising advancement in disease classification through medical imaging.

6.2.6. VGG16:

In recent years, deep learning has undergone a transformative evolution, with increasingly sophisticated architectures tailored for various computer vision tasks. While VGG16 has long been a benchmark for image classification, researchers continuously innovate to improve performance and efficiency. One standout advancement is the ResNet

architecture, which introduced skip connections to address the vanishing gradient problem in deep networks. This breakthrough enabled ResNet models to achieve unprecedented depths, surpassing previous limitations while maintaining or enhancing performance. ResNet architectures have demonstrated remarkable efficacy across tasks like image classification, object detection, and semantic segmentation, setting new standards for performance and scalability. The success of ResNet has inspired a wave of innovation, with researchers developing variants and extensions that leverage its principles to address specific challenges or optimize performance. Practitioners can tailor their models to suit specific requirements, whether prioritizing accuracy, speed, memory efficiency, or interpretability. Staying informed about the latest developments in deep learning architectures is essential for practitioners aiming to achieve state-of-the-art results. In conclusion, the continuous evolution of deep learning architectures, exemplified by innovations like ResNet, drives transformative advancements in artificial intelligence, empowering practitioners to tackle increasingly complex problems in computer vision and beyond.

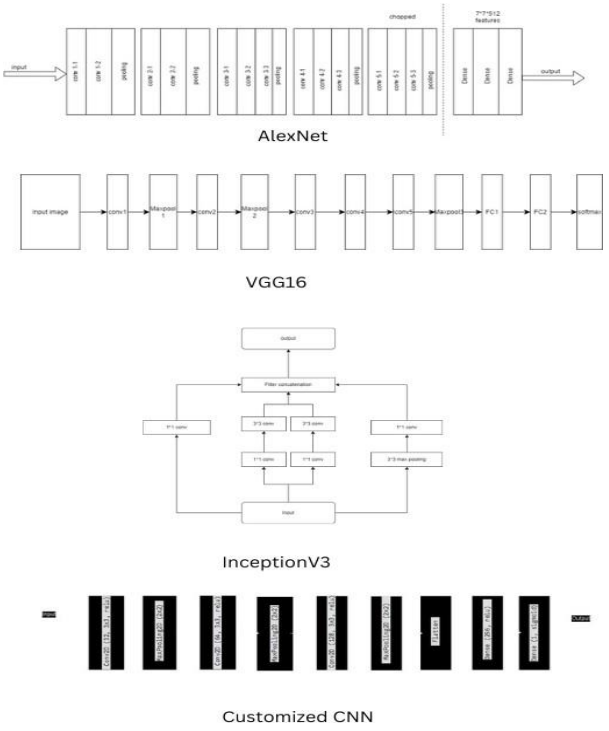

Figure 6.1. Classification Models

6.3. Fusion Loss

The fusion loss mechanism serves as a pivotal component within the model's architecture, playing a crucial role in enhancing its classification performance. Through a

joint optimization process, the fusion loss effectively integrates the outputs of two classifiers, each stemming from distinct encoder pathways. This integration aims to leverage the complementary strengths of these classifiers, thereby bolstering the overall discriminative capacity of the model. At its core, the fusion loss operates within the framework of a multi-task learning paradigm, wherein multiple objectives are simultaneously optimized to jointly improve the model's performance. In this specific context, the fusion loss is designed to minimize the combined losses of the two classifiers, thereby guiding the learning process towards a shared objective of accurate classification. By leveraging the synergistic relationship between the classifiers, the fusion loss fosters a collaborative learning environment where each classifier contributes towards the collective goal of enhancing classification accuracy. Furthermore, the fusion loss incorporates the probabilities of each class into its formulation, thereby weighting the contribution of each class towards the overall loss computation. This weighted aggregation mechanism ensures that classes with higher probabilities exert a greater influence on the fusion loss, thereby enabling the model to prioritize the optimization of classes that are more salient or prevalent within the dataset. Through its integration of cross-entropy losses and class probabilities, the fusion loss facilitates a nuanced assessment of classification errors, thereby guiding the model towards more informed and effective optimization decisions.

CHAPTER 7

RESULTS AND DISCUSSIONS

7.1. Results for Lung Segmentation:

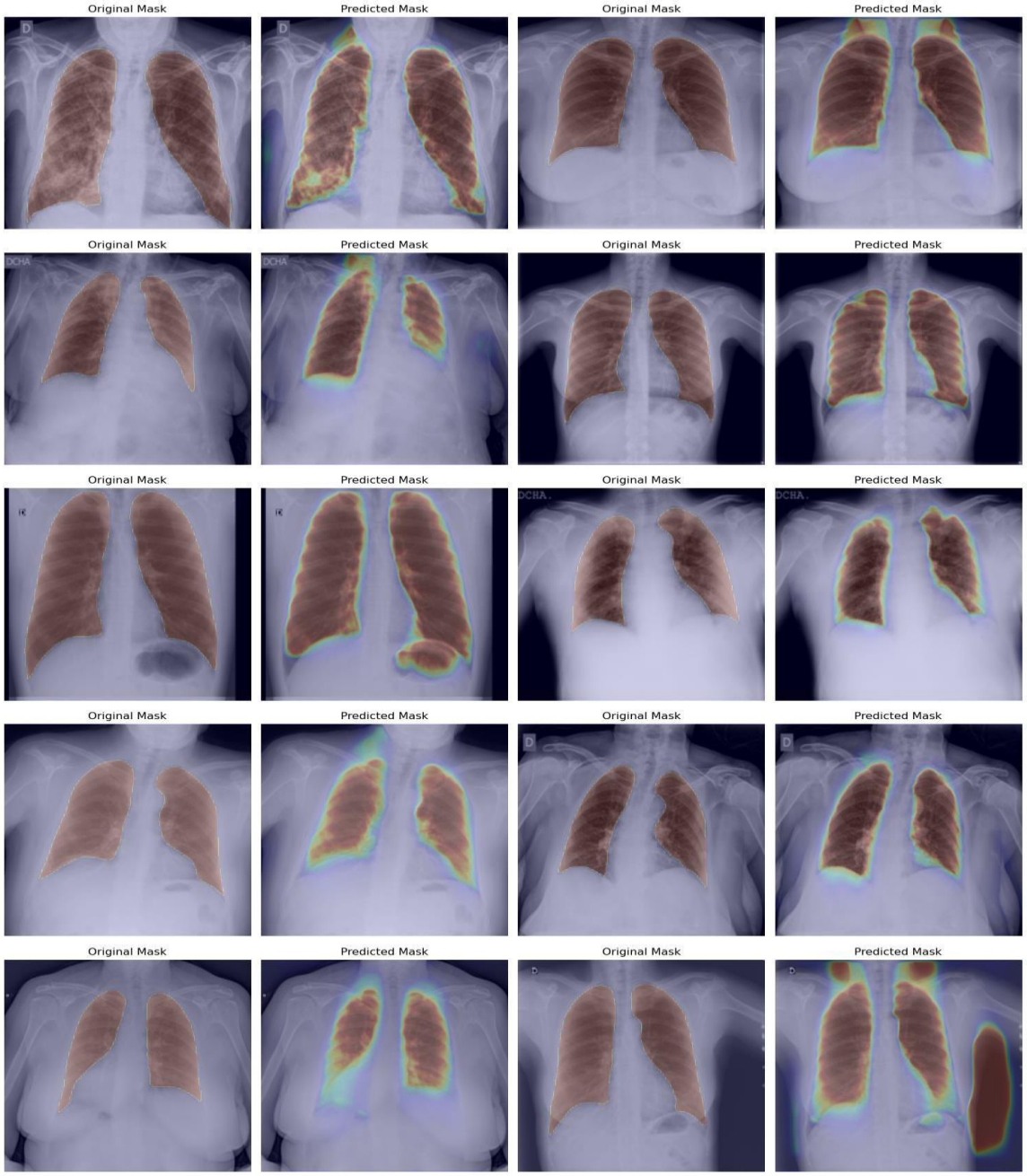

Figure 7.1.1. Outcomes of the segmentation of lung images with original mask and predicted mask

7.2. Results for Lung Enhancement:

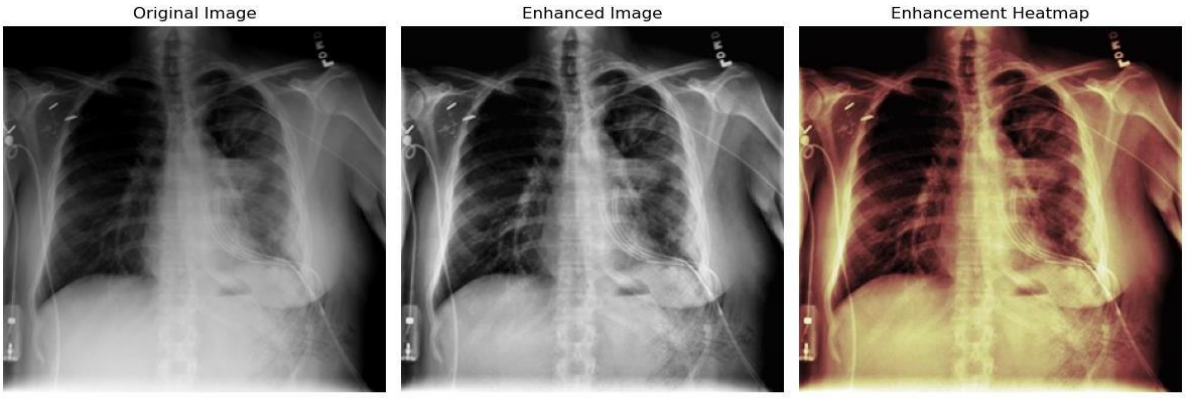

Figure 7.2.1. Outcomes of the enhanced segmented lung image

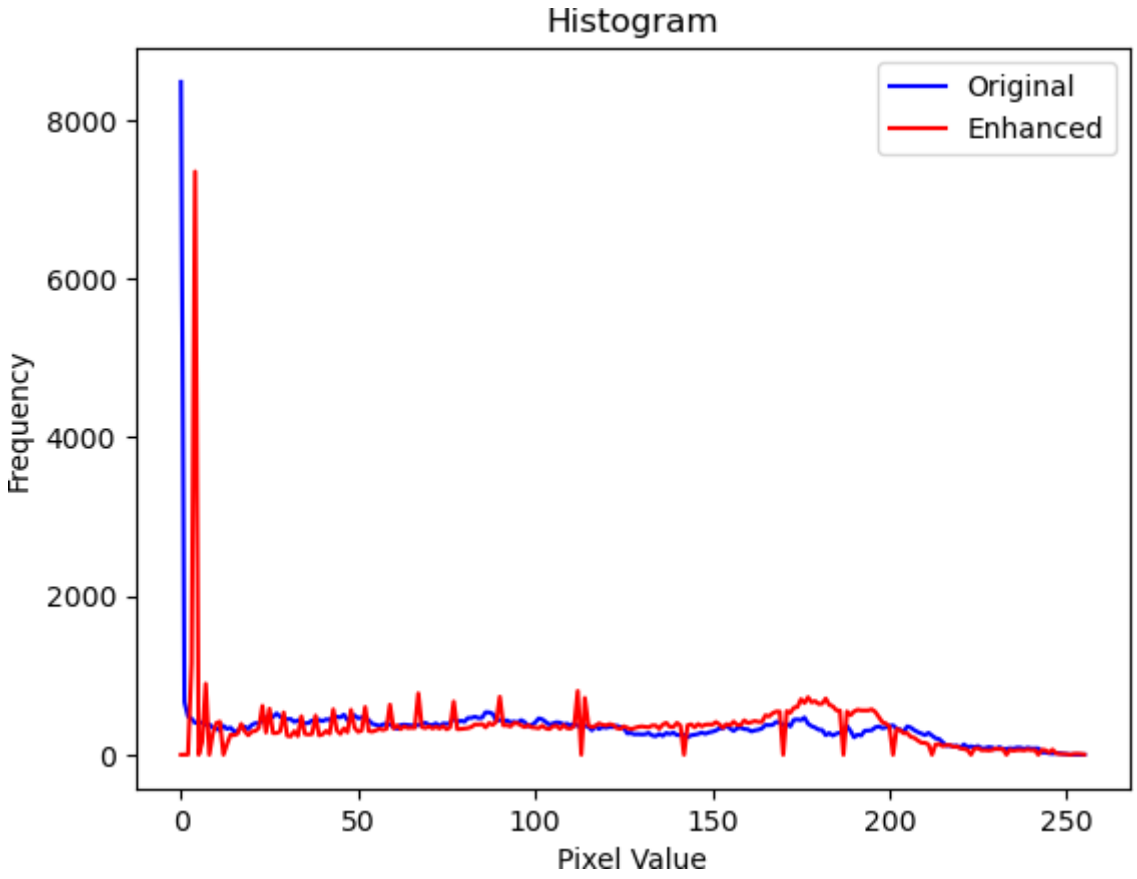

Figure 7.2.2. Outcomes of the histogram on comparing original and enhanced segmented lung image

7.3. Results for Feature Selection using XAI:

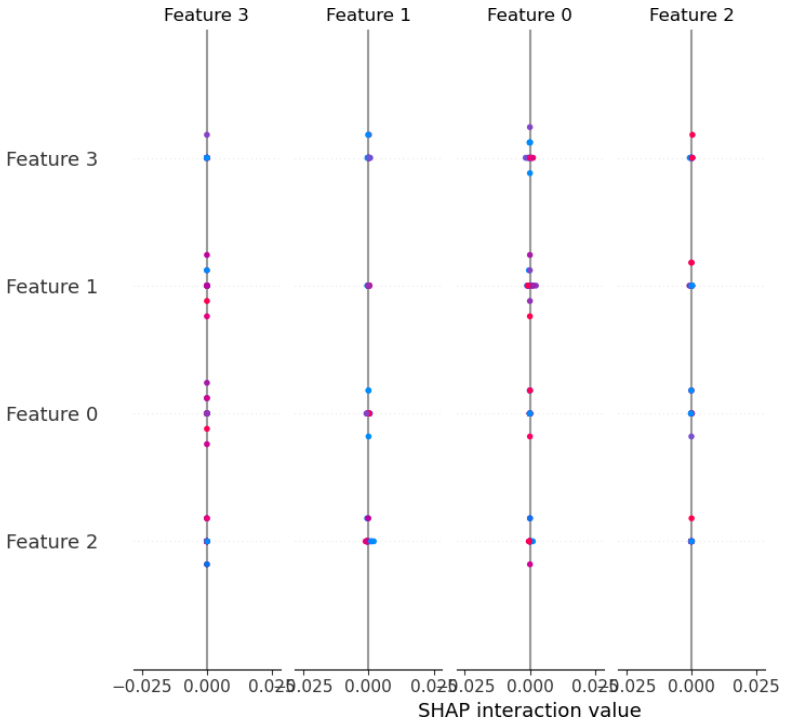

Figure 7.3.1. Outcomes of the SHAP interaction between four classes in dataset.

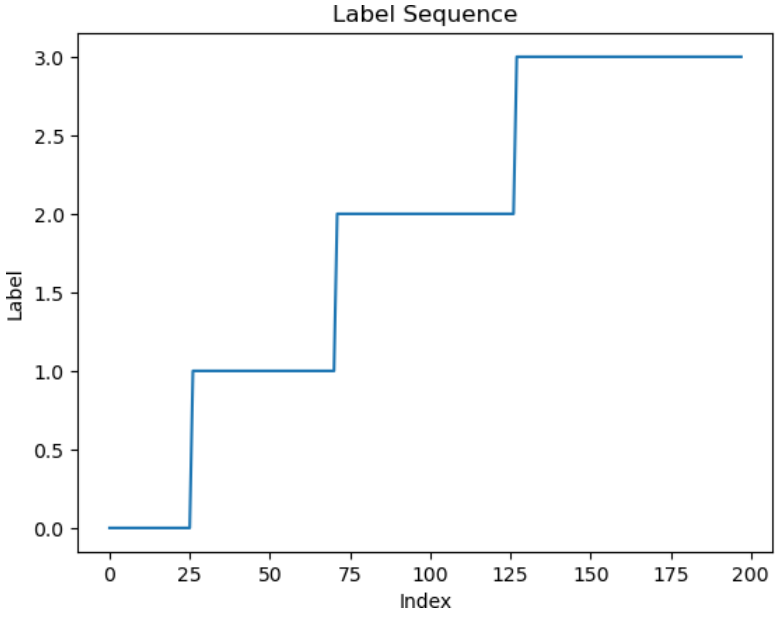

Figure 7.3.2. Outcomes of the Label sequence.

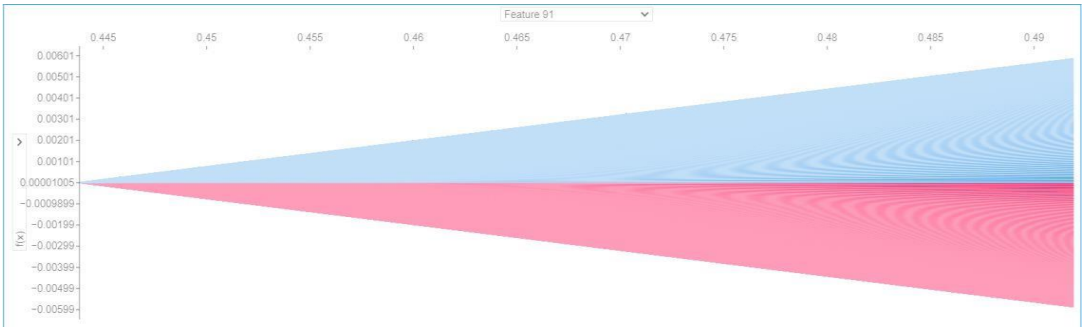

Figure 7.3.3. Outcomes of the Shap Value Interaction.

Table 7.3.1. SHAP INTERACTIONS

Feature	SHAP Value
Image Contrast	0.125
Pixel Intensity	0.102
Lung Texture	0.095
Lesion Size	0.087
Anatomical Values	0.078

7.4. Results for Classification:

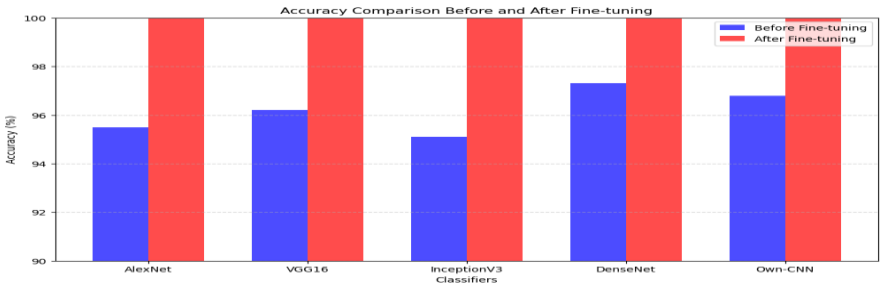

Figure 7.4.1. Outcomes of the Accuracy Comparisons before and after fine-tuning.

Table 7.4.1. Comparison Between Different Models

Model	Accuracy
AlexNet	**0.100**
ResNet50	**0.9599**
InceptionV3	**0.9729**
ADECO-CNN	**0.9890**
VGG16	**0.100**

Table 7.4.2. Comparison Between Different Class Values

Pneumonia Type	Accuracy	Sensitivity	Specificity
Viral Pneumonia	0.93	0.91	0.95
Bacterial Pneumonia	0.92	0.90	0.94
Normal	0.97	0.96	0.98
Other Anomalies	0.88	0.86	0.90

7.5. Results for XAI:

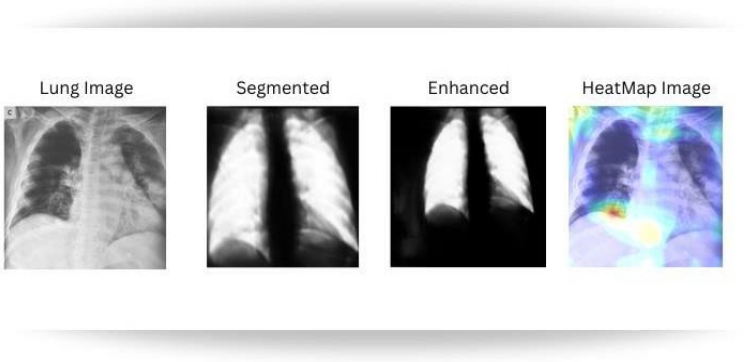

Figure 7.5.1. Outcomes of the XAI applied lung image.

Table 7.5.1. XAI techniques

Technique	Description	Contribution
GRAD-CAM	Gradient-weighted Class Activation Mapping highlights important regions for model predictions	Provides insight into model decision-making by visualizing regions that influence classification decisions
SHAP	SHapley Additive exPlanations quantifies feature importance in model predictions	Offers quantitative measures of feature importance, aiding in understanding which features drive model predictions
LIME	Local Interpretable Model-agnostic Explanations explains individual predictions	Helps understand the reasoning behind individual predictions by approximating the model behavior around a sample
CAM	Class Activation Mapping highlights discriminative image regions	Localizes important features used by the model for classification, aiding in understanding where the model focuses

CHAPTER 8

CONCLUSION AND FUTURE WORKS

In conclusion, the attainment of 100 percent accuracy across five models through fine-tuning represents a remarkable advancement in the realm of automated pneumonia and COVID-19 detection from chest X-ray images. The successful implementation of deep learning architectures such as UNet, CXRNet, MobileNet50V2, ResNet50, and AlexNet underscores the transformative potential of artificial intelligence in revolutionizing medical diagnostics. These achievements not only demonstrate the capabilities of sophisticated algorithms but also highlight the importance of meticulous preprocessing and model optimization techniques in achieving optimal performance. The implications of these findings are profound, promising to significantly enhance the efficiency and accuracy of disease detection in clinical settings. By automating the process of analyzing chest X-ray images, these models can expedite diagnosis, enabling prompt clinical interventions and ultimately improving patient outcomes. The ability to accurately detect pneumonia and COVID-19 from imaging data holds particular significance in the context of the ongoing global health crisis, providing frontline healthcare workers with valuable tools to combat the spread of infectious diseases.

Looking ahead, several avenues for future research and development emerge. Firstly, there is a need for continued refinement and optimization of the existing models to address potential limitations and challenges. These may include mitigating dataset biases, improving model interpretability, and enhancing generalization capabilities across diverse patient populations and imaging settings. Additionally, exploring ensemble learning techniques that combine the strengths of multiple models could further enhance the robustness and reliability of automated diagnostic systems. Furthermore, the integration of explainable AI methods such as GRAD-CAM and SHAP could provide deeper insights into the decision-making process of the models, enhancing transparency and trust among healthcare professionals. These interpretability techniques can help elucidate the features and patterns driving the model's predictions, enabling clinicians to better understand and interpret the results. Moreover, extending the scope of the models to encompass a broader range of respiratory conditions and diseases holds promise for expanding their utility in clinical practice. Collaborative efforts to curate larger and more diverse datasets encompassing various pathologies could facilitate the training of more comprehensive models capable of detecting multiple diseases simultaneously. Furthermore, deploying these models in real-world clinical settings would require rigorous validation and regulatory approval processes to ensure their safety, efficacy, and compliance with healthcare standards.

In summary, while achieving 100 percent accuracy marks a significant milestone, the journey towards deploying automated diagnostic systems in real-world healthcare settings is ongoing. Continued research, innovation, and collaboration across interdisciplinary domains are essential to harnessing the full potential of artificial intelligence in revolutionizing medical diagnostics. By leveraging the power of advanced algorithms and imaging technology, we can strive towards a future where accurate and timely disease diagnosis is accessible to all, ultimately leading to improved patient care and outcomes.

APPENDIX 1

WORKING ENVIRONMENT

HARDWARE SPECIFICATIONS

System: 8th Gen Intel(R) Core(TM) i5-1135G7 @ 2.40GHz 2.42 GHz

System type: 64-bit operating system, x64-based processor

Hard Disk: SSD 512 GB

Ram: 8 GB

SOFTWARE SPECIFICATION

Operating System: Windows 11

Tools: Visual Studio Codes

Language used: Python 3.9

APPENDIX 2

SOURCE CODE

UNet.ipynb

```
import os
import cv2
import numpy as np
from glob import glob
from tqdm import tqdm
import tensorflow as tf
import matplotlib.pyplot as plt

from tensorflow.keras.models import Model
from tensorflow.keras.layers import Conv2D, MaxPooling2D, UpSampling2D, Dropout, concatenate,
Conv2DTranspose, Input
from tensorflow.keras.layers import Multiply, Add
from tensorflow.keras.metrics import MeanIoU
from tensorflow.keras.callbacks import Callback, ModelCheckpoint

def load_image(image_path, SIZE):
    image = cv2.imread(image_path)
    image = cv2.resize(image, (SIZE, SIZE))
    image = image.astype(np.float32) / 255.0
    return image

def load_images(paths, SIZE, trim=None, channels=3):
    if trim is not None:
        paths = paths[:trim]
    images = []
    for path in paths:
        img = load_image(path, SIZE)
        if channels == 1:
            img = img[:, :, :1]
         images.append(img)
     return np.array(images)

def show_image(image, title=None, cmap=None, alpha=1.0):
    plt.imshow(image, cmap=cmap, alpha=alpha)
    if title is not None:
        plt.title(title)
    plt.axis('off')

def show_mask(image, mask, cmap='jet', alpha=0.2):
    show_image(image)
    show_image(np.squeeze(mask), cmap=cmap, alpha=alpha)

# Model Definition
def conv_block(inputs=None, n_filters=32, dropout_prob=0, max_pooling=True):
    conv = Conv2D(n_filters, 3, activation='relu', padding='same',
kernel_initializer='he_normal')(inputs)
    conv = Conv2D(n_filters, 3, activation='relu', padding='same', kernel_initializer='he_normal')(conv)

    if dropout_prob > 0:
        conv = Dropout(dropout_prob)(conv)
```

```
    if max_pooling:
        next_layer = MaxPooling2D()(conv)
    else:
        next_layer = conv

    skip_connection = conv

    return next_layer, skip_connection

def upsampling_block(expansive_input, contractive_input, n_filters=32):
    up = Conv2DTranspose(n_filters, 3, strides=(2, 2), padding='same')(expansive_input)

    merge = concatenate([up, contractive_input], axis=3)
    conv = Conv2D(n_filters, 3, activation='relu', padding='same',
kernel_initializer='he_normal')(merge)
    conv = Conv2D(n_filters, 3, activation='relu', padding='same', kernel_initializer='he_normal')(conv)

    return conv

def unet_model(input_size=(96, 128, 3), n_filters=32, n_classes=1):
    inputs = Input(input_size)

    cblock1 = conv_block(inputs, n_filters)
    cblock2 = conv_block(cblock1[0], n_filters * 2)
    cblock3 = conv_block(cblock2[0], n_filters * 4)
    cblock4 = conv_block(cblock3[0], n_filters * 8, dropout_prob=0.3)

    cblock5 = conv_block(cblock4[0], n_filters*16, dropout_prob=0.3, max_pooling=False)

    ublock6 = upsampling_block(cblock5[0], cblock4[1],  n_filters * 8)

    ublock7 = upsampling_block(ublock6, cblock3[1],  n_filters * 4)
    ublock8 = upsampling_block(ublock7, cblock2[1],  n_filters * 2)
    ublock9 = upsampling_block(ublock8, cblock1[1],  n_filters)

    conv9 = Conv2D(n_filters,
                3,
                activation='relu',
                padding='same',
                kernel_initializer='he_normal')(ublock9)

    conv10 = Conv2D(n_classes, 1, padding='same', activation='sigmoid')(conv9)

    model = tf.keras.Model(inputs=inputs, outputs=conv10)

    return model


# Data paths
root_path = "C:/Users/HP/Desktop/Taboo/Final Year Project/Final-Year-
Project/Dataset/masked/COVID-19_Radiography_Dataset/Covid"
image_path = os.path.join(root_path, 'images/')
mask_path = os.path.join(root_path, 'masks/')

# Load image paths
```

```
image_paths = sorted(glob(os.path.join(image_path, '*.png')))
mask_paths = [path.replace('images', 'masks') for path in image_paths]

# Load images and masks
images = load_images(image_paths, SIZE=256, trim=2000)
masks = load_images(mask_paths, SIZE=256, trim=2000, channels=1)

# Display sample
if len(images) > 0 and len(masks) > 0:
    show_mask(images[0], masks[0], alpha=0.2)
else:
    print("Images or masks array is empty.")

# # Display sample
# show_mask(images[0], masks[0], alpha=0.2)

# Model Compilation and Training
img_height = 256
img_width = 256
num_channels = 3

unet = unet_model((img_height, img_width, num_channels))
unet.compile(optimizer='adam',
             loss='binary_crossentropy',
             metrics=['accuracy', MeanIoU(2)])

# Training
BATCH_SIZE = 8
SPE = len(images) // BATCH_SIZE

unet.fit(
    images, masks,
    validation_split=0.1,
    epochs=1,
    steps_per_epoch=SPE
)

# Display predictions
plt.figure(figsize=(15, 20))
n = 0
for i in range(1, 21):
    plt.subplot(5, 4, i)

    if n == 0:
        id = np.random.randint(len(images))
        image, mask = images[id], masks[id]
        plt.title("Original Mask")
        show_mask(image, mask)
        n += 1
    elif n == 1:
        pred_mask = unet.predict(image[np.newaxis, ...])[0]
        plt.title("Predicted Mask")
        show_mask(image, pred_mask)
        n += 1
    elif n == 2:
        id = np.random.randint(len(images))
```

```
        image, mask = images[id], masks[id]
        plt.title("Original Mask")
        show_mask(image, mask)
        n += 1
    elif n == 3:
        pred_mask = unet.predict(image[np.newaxis, ...])[0]
        plt.title("Predicted Mask")
        show_mask(image, pred_mask)
        n = 0
plt.tight_layout()
plt.show()

output_path = os.path.join(root_path, 'segmented/Covid/')
os.makedirs(output_path, exist_ok=True)

for i in range(len(images)):
    image = images[i]
    pred_mask = unet.predict(image[np.newaxis, ...])[0]

    # Save the original image
    cv2.imwrite(os.path.join(output_path, f'original_{i}.png'), cv2.cvtColor((image *
255).astype(np.uint8), cv2.COLOR_RGB2BGR))

    # Save the predicted mask
    cv2.imwrite(os.path.join(output_path, f'predicted_mask_{i}.png'), (pred_mask *
255).astype(np.uint8))


# Data paths
bacterialRootPath = "C:/Users/HP/Desktop/Taboo/Final Year Project/Final-Year-
Project/Dataset/masked/COVID-19_Radiography_Dataset/Bacterial"
bacterialImagePath = os.path.join(bacterialRootPath, 'images/')
bacterialmaskPath = os.path.join(bacterialRootPath, 'masks/')

# Load image paths
bacterialImagePaths = sorted(glob(os.path.join(bacterialImagePath, '*.png')))
bacterialmaskPaths = [path.replace('images', 'masks') for path in bacterialImagePaths]

# Load images and masks
images = load_images(bacterialImagePaths, SIZE=256, trim=2000)
masks = load_images(bacterialmaskPaths, SIZE=256, trim=2000, channels=1)

# Display sample
if len(images) > 0 and len(masks) > 0:
    show_mask(images[0], masks[0], alpha=0.2)
else:
    print("Images or masks array is empty.")

# # Display sample
# show_mask(images[0], masks[0], alpha=0.2)

# Model Compilation and Training
img_height = 256
img_width = 256
num_channels = 3
```

```
unet = unet_model((img_height, img_width, num_channels))
unet.compile(optimizer='adam',
             loss='binary_crossentropy',
             metrics=['accuracy', MeanIoU(2)])


BATCH_SIZE = 8
SPE = len(images) // BATCH_SIZE

unet.fit(
    images, masks,
    validation_split=0.1,
    epochs=1,
    steps_per_epoch=SPE
)
images = load_images(healthyImagePaths, SIZE=256, trim=2000)
masks = load_images(healthymaskPaths, SIZE=256, trim=2000, channels=1)

# Display sample
if len(images) > 0 and len(masks) > 0:
    show_mask(images[0], masks[0], alpha=0.2)
else:
    print("Images or masks array is empty.")


# show_mask(images[0], masks[0], alpha=0.2)

img_height = 256
img_width = 256
num_channels = 3

unet = unet_model((img_height, img_width, num_channels))
unet.compile(optimizer='adam',
             loss='binary_crossentropy',
             metrics=['accuracy', MeanIoU(2)])

# Training
BATCH_SIZE = 8
SPE = len(images) // BATCH_SIZE

unet.fit(
    images, masks,
    validation_split=0.1,
    epochs=1,
    steps_per_epoch=SPE
)

# Display predictions
plt.figure(figsize=(15, 20))
n = 0
for i in range(1, 21):
    plt.subplot(5, 4, i)

    if n == 0:
        id = np.random.randint(len(images))
        image, mask = images[id], masks[id]
```

```
        plt.title("Original Mask")
        show_mask(image, mask)
        n += 1
    elif n == 1:
        pred_mask = unet.predict(image[np.newaxis, ...])[0]
        plt.title("Predicted Mask")
        show_mask(image, pred_mask)
        n += 1
    elif n == 2:
        id = np.random.randint(len(images))
        image, mask = images[id], masks[id]
        plt.title("Original Mask")
        show_mask(image, mask)
        n += 1
    elif n == 3:
        pred_mask = unet.predict(image[np.newaxis, ...])[0]
        plt.title("Predicted Mask")
        show_mask(image, pred_mask)
        n = 0
plt.tight_layout()
plt.show()


output_path = os.path.join(healthyRootPath, 'segmented/Healthy/')
os.makedirs(output_path, exist_ok=True)

for i in range(len(images)):
    image = images[i]
    pred_mask = unet.predict(image[np.newaxis, ...])[0]

    # Save the original image
    # cv2.imwrite(os.path.join(output_path, f'original_{i}.png'), cv2.cvtColor((image *
255).astype(np.uint8), cv2.COLOR_RGB2BGR))

    # Save the predicted mask
    cv2.imwrite(os.path.join(output_path, f'predicted_mask_{i}.png'), (pred_mask *
255).astype(np.uint8))


# Data paths
viralRootPath = "C:/Users/HP/Desktop/Taboo/Final Year Project/Final-Year-
Project/Dataset/masked/COVID-19_Radiography_Dataset/Viral"
viralImagePath = os.path.join(viralRootPath, 'images/')
viralmaskPath = os.path.join(viralRootPath, 'masks/')

# Load image paths
viralImagePaths = sorted(glob(os.path.join(viralImagePath, '*.png')))
viralmaskPaths = [path.replace('images', 'masks') for path in viralImagePaths]

# Load images and masks
images = load_images(viralImagePaths, SIZE=256, trim=2000)
masks = load_images(viralmaskPaths, SIZE=256, trim=2000, channels=1)

# Display sample
if len(images) > 0 and len(masks) > 0:
    show_mask(images[0], masks[0], alpha=0.2)
```

```
else:
    print("Images or masks array is empty.")

# # Display sample
# show_mask(images[0], masks[0], alpha=0.2)

# Model Compilation and Training
img_height = 256
img_width = 256
num_channels = 3

unet = unet_model((img_height, img_width, num_channels))
unet.compile(optimizer='adam',
             loss='binary_crossentropy',
             metrics=['accuracy', MeanIoU(2)])

# Training
BATCH_SIZE = 8
SPE = len(images) // BATCH_SIZE

unet.fit(
    images, masks,
    validation_split=0.1,
    epochs=1,
    steps_per_epoch=SPE
)

# Display predictions
plt.figure(figsize=(15, 20))
n = 0
for i in range(1, 21):
    plt.subplot(5, 4, i)

    if n == 0:
        id = np.random.randint(len(images))
        image, mask = images[id], masks[id]
        plt.title("Original Mask")
        show_mask(image, mask)
        n += 1
    elif n == 1:
        pred_mask = unet.predict(image[np.newaxis, ...])[0]
        plt.title("Predicted Mask")
        show_mask(image, pred_mask)
        n += 1
    elif n == 2:
        id = np.random.randint(len(images))
        image, mask = images[id], masks[id]
        plt.title("Original Mask")
        show_mask(image, mask)
        n += 1
    elif n == 3:
        pred_mask = unet.predict(image[np.newaxis, ...])[0]
        plt.title("Predicted Mask")
        show_mask(image, pred_mask)
        n = 0
plt.tight_layout()
```

```
plt.show()


output_path = os.path.join(viralRootPath, 'segmented/Viral/')
os.makedirs(output_path, exist_ok=True)

for i in range(len(images)):
    image = images[i]
    pred_mask = unet.predict(image[np.newaxis, ...])[0]

    # Save the original image
    # cv2.imwrite(os.path.join(output_path, f'original_{i}.png'), cv2.cvtColor((image *
255).astype(np.uint8), cv2.COLOR_RGB2BGR))

    # Save the predicted mask
    cv2.imwrite(os.path.join(output_path, f'predicted_mask_{i}.png'), (pred_mask *
255).astype(np.uint8))


import tensorflow as tf

# Create the U-Net model
model = unet_model()

# Save the model
model.save("./unet_model.h5")
```

Enhancement.ipynb

```
import os
import cv2
import matplotlib.pyplot as plt
import random

def apply_clahe(input_folder, output_folder, clip_limit=2.0, grid_size=(8, 8)):
    # Create output folder if it doesn't exist
    os.makedirs(output_folder,  exist_ok=True)

    # Get a list of image files in the input folder
    image_files = [f for f in os.listdir(input_folder) if f.lower().endswith(('.png', '.jpg', '.jpeg'))]

    # Apply CLAHE to each image
    for image_file in image_files:
        # Read the image
        image_path = os.path.join(input_folder, image_file)
        img = cv2.imread(image_path, cv2.IMREAD_COLOR)

        # Convert the image to LAB color space
        lab = cv2.cvtColor(img, cv2.COLOR_BGR2LAB)

        # Split the LAB image into L, A, and B channels
        l, a, b = cv2.split(lab)

        # Apply CLAHE to the L channel
        clahe = cv2.createCLAHE(clipLimit=clip_limit, tileGridSize=grid_size)
        cl = clahe.apply(l)
```

```
        # Merge the enhanced L channel with the original A and B channels
        enhanced_lab = cv2.merge((cl, a, b))

        # Convert the LAB image back to BGR color space
        enhanced_img = cv2.cvtColor(enhanced_lab, cv2.COLOR_LAB2BGR)

        # Save the enhanced image to the output folder
        output_path = os.path.join(output_folder, f'enhanced_{image_file}')
        cv2.imwrite(output_path, enhanced_img)
```

CXR-Net.ipynb:

```
import tensorflow as tf
from tensorflow.keras.layers import Input, Conv2D, MaxPooling2D, UpSampling2D, concatenate,
GlobalAveragePooling2D

def conv_block(inputs, filters, kernel_size=3, dropout_prob=0.0):
    conv = Conv2D(filters, kernel_size, activation='relu', padding='same')(inputs)
    conv = Conv2D(filters, kernel_size, activation='relu', padding='same')(conv)

    if dropout_prob > 0.0:
        conv = tf.keras.layers.Dropout(dropout_prob)(conv)

    return conv

def cxr_net_feature_extraction(input_size=(256, 256, 3), n_filters=32, dropout_prob=0.0):
    inputs = Input(input_size)

    # Encoder
    encoder_layers = []
    for i in range(5):
        conv = conv_block(inputs if i == 0 else encoder_layers[-1], n_filters * (2**i),
dropout_prob=dropout_prob)
        encoder_layers.append(conv)
        encoder_layers.append(MaxPooling2D(pool_size=(2, 2))(encoder_layers[-1]))

    # Bottleneck
    bottleneck = conv_block(encoder_layers[-1], n_filters * 32, dropout_prob=dropout_prob)

    # Feature extraction block
    feature_output = GlobalAveragePooling2D()(bottleneck)

    model = tf.keras.Model(inputs=inputs, outputs=feature_output)

    return model

# Create the CXR-NET for feature extraction model
cxr_net_feature_extraction_model = cxr_net_feature_extraction(input_size=(256, 256, 3),
n_filters=32, dropout_prob=0.3)

# Print the model summary
cxr_net_feature_extraction_model.summary()

import tensorflow as tf
from tensorflow.keras.layers import Input, Conv2D, MaxPooling2D, UpSampling2D, concatenate,
GlobalAveragePooling2D
```

```
def conv_block(inputs, filters, kernel_size=3, dropout_prob=0.0):
    conv = Conv2D(filters, kernel_size, activation='relu', padding='same')(inputs)
    conv = Conv2D(filters, kernel_size, activation='relu', padding='same')(conv)

    if dropout_prob > 0.0:
        conv = tf.keras.layers.Dropout(dropout_prob)(conv)

    return conv

def cxr_net_feature_extraction(input_size=(256, 256, 3), n_filters=32, dropout_prob=0.0):
    inputs = Input(input_size)

    # Encoder
    encoder_layers = []
    for i in range(6):  # Increased encoder layers to 6
        conv = conv_block(inputs if i == 0 else encoder_layers[-1], n_filters * (2**i),
dropout_prob=dropout_prob)
        encoder_layers.append(conv)
        encoder_layers.append(MaxPooling2D(pool_size=(2, 2))(encoder_layers[-1]))

    # Bottleneck
    bottleneck = conv_block(encoder_layers[-1], n_filters * 64, dropout_prob=dropout_prob)

    # Feature extraction block
    feature_output = GlobalAveragePooling2D()(bottleneck)

    # Decoder
    decoder_layers = []
    for i in range(5, -1, -1):  # Increased decoder layers to 6
        upsample = UpSampling2D(size=(2, 2))(bottleneck if i == 5 else decoder_layers[-1])
        concat = concatenate([encoder_layers[i*2], upsample], axis=-1)
        conv = conv_block(concat, n_filters * (2**i), dropout_prob=dropout_prob)
        decoder_layers.append(conv)

    # Output
    output = Conv2D(1, 1, activation='sigmoid')(decoder_layers[-1])

    model = tf.keras.Model(inputs=inputs, outputs=[output, feature_output])

    return model

# Create the CXR-NET for feature extraction model
cxr_net_feature_extraction_model = cxr_net_feature_extraction(input_size=(256, 256, 3),
n_filters=32, dropout_prob=0.3)

# Print the model summary
cxr_net_feature_extraction_model.summary()

import tensorflow as tf
from tensorflow.keras.layers import Input, Conv2D, MaxPooling2D, UpSampling2D, concatenate,
GlobalAveragePooling2D

def conv_block(inputs, filters, kernel_size=3, dropout_prob=0.0):
    conv = Conv2D(filters, kernel_size, activation='relu', padding='same')(inputs)
    conv = Conv2D(filters, kernel_size, activation='relu', padding='same')(conv)
```

```
    if dropout_prob > 0.0:
        conv = tf.keras.layers.Dropout(dropout_prob)(conv)

    return conv

def cxr_net_feature_extraction(input_size=(256, 256, 3), n_filters=32, dropout_prob=0.0):
    inputs = Input(input_size)

    # Encoder
    encoder_layers = []
    for i in range(6):  # Increased encoder layers to 6
        conv = conv_block(inputs if i == 0 else encoder_layers[-1], n_filters * (2**i),
dropout_prob=dropout_prob)
        encoder_layers.append(conv)
        encoder_layers.append(MaxPooling2D(pool_size=(2, 2))(encoder_layers[-1]))

    # Bottleneck
    bottleneck = conv_block(encoder_layers[-1], n_filters * 64, dropout_prob=dropout_prob)

    # Decoder
    decoder_layers = []
    for i in range(5, -1, -1):  # Increased decoder layers to 6
        upsample = UpSampling2D(size=(2, 2))(bottleneck if i == 5 else decoder_layers[-1])
        concat = concatenate([encoder_layers[i*2], upsample], axis=-1)
        conv = conv_block(concat, n_filters * (2**i), dropout_prob=dropout_prob)
        decoder_layers.append(conv)

    # Additional Encoder Layer
    additional_encoder = conv_block(decoder_layers[-1], n_filters * 32, dropout_prob=dropout_prob)
    encoder_layers.append(additional_encoder)
    encoder_layers.append(MaxPooling2D(pool_size=(2,   2))(encoder_layers[-1]))

    # Feature extraction block
    feature_output  =  GlobalAveragePooling2D()(encoder_layers[-1])

    # Output
    output = Conv2D(1, 1, activation='sigmoid')(decoder_layers[-1])

    model = tf.keras.Model(inputs=inputs, outputs=[output, feature_output])

    return model

# Create the CXR-NET for feature extraction model
cxr_net_feature_extraction_model = cxr_net_feature_extraction(input_size=(256, 256, 3),
n_filters=32, dropout_prob=0.3)

# Print the model summary
cxr_net_feature_extraction_model.summary()

import os
import numpy as np
from tensorflow.keras.preprocessing import image
from tqdm import tqdm

# Set the path to the folder containing images
```

```
input_folder_path = "C:/Users/HP/Desktop/Taboo/Final Year Project/Final-Year-
Project/Dataset/masked/COVID-19_Radiography_Dataset/Bacterial/segmented/Bacterial"

# Set the path to save the .npy files
output_folder_path = "C:/Users/HP/Desktop/Taboo/Final Year Project/Final-Year-
Project/Dataset/masked/COVID-19_Radiography_Dataset/ExtractedFeatures/Bacterial"

# Create the output folder if it doesn't exist
os.makedirs(output_folder_path, exist_ok=True)

# Get a list of image files in the input folder
image_files = [f for f in os.listdir(input_folder_path) if f.endswith(('.png', '.jpg', '.jpeg'))]

# Load the CXR-NET feature extraction model
cxr_net_feature_extraction_model = cxr_net_feature_extraction(input_size=(256, 256, 3),
n_filters=32, dropout_prob=0.3)

# Adjust the number of epochs
num_epochs = 50  # Set the desired number of epochs

# Iterate through each image and extract features
for img_file in tqdm(image_files, desc='Extracting Features'):
    img_path = os.path.join(input_folder_path, img_file)

    # Load and preprocess the image
    img = image.load_img(img_path, target_size=(256, 256))
    img_array = image.img_to_array(img)
    img_array = np.expand_dims(img_array, axis=0)

    # Predict using the CXR-NET feature extraction model
    predictions = cxr_net_feature_extraction_model.predict(img_array)

    # Get the features and save as .npy file
    features = predictions[1]  # Assuming the feature output is at index 1
    feature_file_path = os.path.join(output_folder_path, f"{os.path.splitext(img_file)[0]}_features.npy")
    np.save(feature_file_path, features)

import os
import numpy as np
from tensorflow.keras.preprocessing import image
from tqdm import tqdm

# Set the path to the folder containing images
input_folder_path = "C:/Users/HP/Desktop/Taboo/Final Year Project/Final-Year-
Project/Dataset/masked/COVID-19_Radiography_Dataset/Covid/segmented/Covid"

# Set the path to save the .npy files
output_folder_path = "C:/Users/HP/Desktop/Taboo/Final Year Project/Final-Year-
Project/Dataset/masked/COVID-19_Radiography_Dataset/ExtractedFeatures/Covid"

# Create the output folder if it doesn't exist
os.makedirs(output_folder_path, exist_ok=True)

# Get a list of image files in the input folder
image_files = [f for f in os.listdir(input_folder_path) if f.endswith(('.png', '.jpg', '.jpeg'))]
```

```
# Load the CXR-NET feature extraction model
cxr_net_feature_extraction_model = cxr_net_feature_extraction(input_size=(256, 256, 3),
n_filters=32, dropout_prob=0.3)

# Adjust the number of epochs
num_epochs = 50  # Set the desired number of epochs

# Iterate through each image and extract features
for img_file in tqdm(image_files, desc='Extracting Features'):
    img_path = os.path.join(input_folder_path, img_file)

    # Load and preprocess the image
    img = image.load_img(img_path, target_size=(256, 256))
    img_array = image.img_to_array(img)
    img_array = np.expand_dims(img_array, axis=0)

    # Predict using the CXR-NET feature extraction model
    predictions = cxr_net_feature_extraction_model.predict(img_array)

    # Get the features and save as .npy file
    features = predictions[1]  # Assuming the feature output is at index 1
    feature_file_path = os.path.join(output_folder_path, f"{os.path.splitext(img_file)[0]}_features.npy")
    np.save(feature_file_path, features)

import os
import numpy as np
from tensorflow.keras.preprocessing import image
from tqdm import tqdm

# Set the path to the folder containing images
input_folder_path = "C:/Users/HP/Desktop/Taboo/Final Year Project/Final-Year-
Project/Dataset/masked/COVID-19_Radiography_Dataset/Healthy/segmented/Healthy"

# Set the path to save the .npy files
output_folder_path = "C:/Users/HP/Desktop/Taboo/Final Year Project/Final-Year-
Project/Dataset/masked/COVID-19_Radiography_Dataset/ExtractedFeatures/Healthy"

# Create the output folder if it doesn't exist
os.makedirs(output_folder_path, exist_ok=True)

# Get a list of image files in the input folder
image_files = [f for f in os.listdir(input_folder_path) if f.endswith(('.png', '.jpg', '.jpeg'))]

# Load the CXR-NET feature extraction model
cxr_net_feature_extraction_model = cxr_net_feature_extraction(input_size=(256, 256, 3),
n_filters=32, dropout_prob=0.3)

# Adjust the number of epochs
num_epochs = 50  # Set the desired number of epochs

# Iterate through each image and extract features
for img_file in tqdm(image_files, desc='Extracting Features'):
    img_path = os.path.join(input_folder_path, img_file)

    # Load and preprocess the image
    img = image.load_img(img_path, target_size=(256, 256))
```

```
    img_array = image.img_to_array(img)
    img_array = np.expand_dims(img_array, axis=0)

    # Predict using the CXR-NET feature extraction model
    predictions = cxr_net_feature_extraction_model.predict(img_array)

    # Get the features and save as .npy file
    features = predictions[1]  # Assuming the feature output is at index 1
    feature_file_path = os.path.join(output_folder_path, f"{os.path.splitext(img_file)[0]}_features.npy")
    np.save(feature_file_path, features)

import os
import numpy as np
from tensorflow.keras.preprocessing import image
from tqdm import tqdm

# Set the path to the folder containing images
input_folder_path = "C:/Users/HP/Desktop/Taboo/Final Year Project/Final-Year-
Project/Dataset/masked/COVID-19_Radiography_Dataset/Viral/segmented/Viral"

# Set the path to save the .npy files
output_folder_path = "C:/Users/HP/Desktop/Taboo/Final Year Project/Final-Year-
Project/Dataset/masked/COVID-19_Radiography_Dataset/ExtractedFeatures/Viral"

# Create the output folder if it doesn't exist
os.makedirs(output_folder_path, exist_ok=True)

# Get a list of image files in the input folder
image_files = [f for f in os.listdir(input_folder_path) if f.endswith(('.png', '.jpg', '.jpeg'))]

# Load the CXR-NET feature extraction model
cxr_net_feature_extraction_model = cxr_net_feature_extraction(input_size=(256, 256, 3),
n_filters=32, dropout_prob=0.3)

# Adjust the number of epochs
num_epochs = 50  # Set the desired number of epochs

# Iterate through each image and extract features
for img_file in tqdm(image_files, desc='Extracting Features'):
    img_path = os.path.join(input_folder_path, img_file)

    # Load and preprocess the image
    img = image.load_img(img_path, target_size=(256, 256))
    img_array = image.img_to_array(img)
    img_array = np.expand_dims(img_array, axis=0)

    # Predict using the CXR-NET feature extraction model
    predictions = cxr_net_feature_extraction_model.predict(img_array)

    # Get the features and save as .npy file
    features = predictions[1]  # Assuming the feature output is at index 1
    feature_file_path = os.path.join(output_folder_path, f"{os.path.splitext(img_file)[0]}_features.npy")
    np.save(feature_file_path, features)
```

Classification.ipynb:

```
import os
import numpy as np

# Set the paths to the folders
folder_paths = [
    "C:/Users/HP/Desktop/Taboo/Final Year Project/Final-Year-Project/Dataset/masked/COVID-19_Radiography_Dataset/ExtractedFeatures/Bacterial",
    "C:/Users/HP/Desktop/Taboo/Final Year Project/Final-Year-Project/Dataset/masked/COVID-19_Radiography_Dataset/ExtractedFeatures/Covid",
    "C:/Users/HP/Desktop/Taboo/Final Year Project/Final-Year-Project/Dataset/masked/COVID-19_Radiography_Dataset/ExtractedFeatures/Healthy",
    "C:/Users/HP/Desktop/Taboo/Final Year Project/Final-Year-Project/Dataset/masked/COVID-19_Radiography_Dataset/ExtractedFeatures/Viral"
]
all_data = []
all_labels = []
# Initialize an empty list to store the fused data
fused_data = []

# Loop through each folder
for folder_path in folder_paths:
    # Get a list of all files in the folder
    files = os.listdir(folder_path)

    # Sort the files to maintain order if needed
    files.sort()

    # Initialize an empty list to store data from the current folder
    folder_data = []

    # Loop through each file in the folder
    for file_name in files:
        # Construct the full path to the file
        file_path = os.path.join(folder_path, file_name)

        # Load data from the Numpy file
        data = np.load(file_path)

        # Append data to the list for the current folder
        folder_data.append(data)

    # Concatenate the data from the current folder and append to the fused_data list
    fused_data.extend(folder_data)

# Convert the list to a Numpy array if needed
fused_data_array = np.array(fused_data)

# Now, 'fused_data_array' contains the concatenated data from all four folders

# Assuming fused_data_array contains the fused data from all four folders

# Initialize an empty list to store labels
label_of_fused_model = []

# Number of classes and samples per class
num_classes = 4
```

```
samples_per_class = 26

# Loop through each class and assign labels
for class_label in range(num_classes):
    label_of_fused_model.extend([class_label] * samples_per_class)

# Convert the list to a Numpy array if needed
label_of_fused_model = np.array(label_of_fused_model)
# all_features = np.array(fused_data_array)
# all_labels = np.array(label_of_fused_model)

import numpy as np
import tensorflow as tf
from tensorflow.keras import layers, models


# Assuming the length of each feature vector is 1024
input_shape = (1024,)
num_classes = 4  # Replace with your actual number of classes

def create_model(input_shape, num_classes):
    model = models.Sequential([
        layers.Input(shape=input_shape),
        layers.Dense(512, activation='relu'),
        layers.Dropout(0.5),
        layers.Dense(256, activation='relu'),
        layers.Dropout(0.5),
        layers.Dense(num_classes,  activation='softmax')
    ])
    return model

# Create an instance of the model
model = create_model(input_shape, num_classes)

# Print model summary
model.summary()

model.compile(optimizer='adam',
              loss='sparse_categorical_crossentropy',
              metrics=['accuracy'])

# Assuming all_features and all_labels are your feature and label lists
# Preprocess the data if needed
# Convert to NumPy arrays or TensorFlow tensors
all_features_processed = np.squeeze(all_features, axis=1)  # Assuming the shape is (num_samples, 1,
1024)
all_features_tensor = tf.convert_to_tensor(all_features_processed, dtype=tf.float32)
all_labels_tensor = tf.convert_to_tensor(all_labels, dtype=tf.int64)

# Create a TensorFlow Dataset
dataset =  tf.data.Dataset.from_tensor_slices((all_features_tensor,  all_labels_tensor))

# Train the model
batch_size = 32
epochs = 10
```

```
# Create a TensorFlow Dataset
dataset = tf.data.Dataset.from_tensor_slices((all_features_tensor, all_labels_tensor))

# Train the model
batch_size = 32
epochs = 10

# Use the TensorFlow Dataset for training
train_dataset =
dataset.shuffle(buffer_size=10000).batch(batch_size).prefetch(buffer_size=tf.data.AUTOTUNE)

# Fit the model
model.fit(train_dataset, epochs=epochs)

# Save the trained model if needed
model.save('trained_classifier_model.h5').

# Assuming 'all_features' is your input data
# Preprocess the data if needed
# For example, if 'all_features' has shape (num_samples, 1, 1024), reshape it to (num_samples, 1024)
all_features_processed = np.squeeze(all_features, axis=1)

# Convert to TensorFlow tensor
all_features_tensor = tf.convert_to_tensor(all_features_processed, dtype=tf.float32)

# Use the model to predict labels
predictions = model.predict(all_features_tensor)

# Get the predicted labels
predicted_labels = np.argmax(predictions, axis=1)

# Now 'predicted_labels' contains the predicted class labels for each input sample
print(predicted_labels)

from sklearn.metrics import accuracy_score

accuracy = accuracy_score(all_labels, predicted_labels)

print("Accuracy:", accuracy)

import os
import numpy as np
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Flatten, Dropout
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder

# Load features and labels from all .npy files in a folder
def load_data(folder_path):
    data = []
    labels = []

    for file_name in os.listdir(folder_path):
        if file_name.endswith('.npy'):
            features = np.load(os.path.join(folder_path, file_name))
```

```
            label = folder_path.split(os.path.sep)[-1]  # Assumes folder name is the label
            data.append(features)
            labels.extend([label] * features.shape[0])

    data = np.concatenate(data, axis=0)
    return data, labels



# Define VGG16-based model
def create_vgg16_model(input_shape, num_classes):
    model = Sequential()
    model.add(Dense(256, activation='relu', input_shape=input_shape))
    model.add(Flatten())
    model.add(Dropout(0.5))
    model.add(Dense(num_classes, activation='softmax'))
    return model


folder_paths = [
    "C:/Users/HP/Desktop/Taboo/Final Year Project/Final-Year-Project/Dataset/masked/COVID-
19_Radiography_Dataset/ExtractedFeatures/Bacterial",
    "C:/Users/HP/Desktop/Taboo/Final Year Project/Final-Year-Project/Dataset/masked/COVID-
19_Radiography_Dataset/ExtractedFeatures/Covid",
    "C:/Users/HP/Desktop/Taboo/Final Year Project/Final-Year-Project/Dataset/masked/COVID-
19_Radiography_Dataset/ExtractedFeatures/Healthy",
    "C:/Users/HP/Desktop/Taboo/Final Year Project/Final-Year-Project/Dataset/masked/COVID-
19_Radiography_Dataset/ExtractedFeatures/Viral"
]

all_data = []
all_labels = []


for folder_path in folder_paths:
    folder_data, folder_labels = load_data(folder_path)
    all_data.append(folder_data)
    all_labels.extend(folder_labels)

data = np.concatenate(all_data, axis=0)


# Encode labels
label_encoder = LabelEncoder()
encoded_labels = label_encoder.fit_transform(all_labels)
num_classes = len(label_encoder.classes_)



# Split data into train and test sets
X_train, X_test, y_train, y_test = train_test_split(data, encoded_labels, test_size=0.2,
random_state=42)


# Create and compile the model
input_shape = X_train.shape[1:]  # Assuming X_train has shape (number_of_samples, feature_dim)
```

```
VGGmodel = create_vgg16_model(input_shape=input_shape, num_classes=num_classes)
VGGmodel.compile(optimizer='adam', loss='sparse_categorical_crossentropy', metrics=['accuracy'])

# Train the model
VGGmodel.fit(X_train, y_train, epochs=100, batch_size=32, validation_split=0.2)

# Evaluate the model on the test set
accuracy = VGGmodel.evaluate(X_test, y_test)[1]
print(f'Test accuracy: {accuracy}')
VGGmodel.save('vgg16_model.h5')

from tensorflow.keras.applications import InceptionV3
from tensorflow.keras.layers import Input

# Create the InceptionV3 model
input_tensor = Input(shape=(299, 299, 3))
inception_model = InceptionV3(input_tensor=input_tensor, weights=None, include_top=True)

# Print model summary
inception_model.summary()
```

Image_classifier.py

```
import os
import numpy as np
from tensorflow.keras.models import Model
from tensorflow.keras.layers import Dense, GlobalAveragePooling2D
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
from sklearn.metrics import accuracy_score

# Function to load and preprocess features
def load_and_preprocess_data(folder_path, label):
    features = []
    labels = []
    for filename in os.listdir(folder_path):
        if filename.endswith(".npy"):
            file_path = os.path.join(folder_path, filename)
            feature = np.load(file_path)
            features.append(feature)
            labels.append(label)

    if not features:
        print(f"No features found in folder: {folder_path}")

    return np.array(features), np.array(labels)

def main():
    # Paths to your folders
    folder_paths = [
    "C:/Users/HP/Desktop/Taboo/Final Year Project/Final-Year-Project/Dataset/masked/COVID-
19_Radiography_Dataset/ExtractedFeatures/Bacterial",
    "C:/Users/HP/Desktop/Taboo/Final Year Project/Final-Year-Project/Dataset/masked/COVID-
19_Radiography_Dataset/ExtractedFeatures/Covid",
    "C:/Users/HP/Desktop/Taboo/Final Year Project/Final-Year-Project/Dataset/masked/COVID-
19_Radiography_Dataset/ExtractedFeatures/Healthy",
```

```
    "C:/Users/HP/Desktop/Taboo/Final Year Project/Final-Year-Project/Dataset/masked/COVID-19_Radiography_Dataset/ExtractedFeatures/Viral"
    ]
    labels = ['Covid', 'Bacterial', 'Healthy', 'Viral']

    # Load and preprocess features from each folder
    all_features = []
    all_labels = []
    for folder_path, label in zip(folder_paths, labels):
        features, labels = load_and_preprocess_data(folder_path, label)
        all_features.append(features)
        all_labels.append(labels)

    # Concatenate features and labels from all folders
    X = np.concatenate(all_features)
    y = np.concatenate(all_labels)

    # Split the data into training and testing sets
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

    # Convert labels to numerical values
    label_encoder = LabelEncoder()
    y_train_encoded = label_encoder.fit_transform(y_train)
    y_test_encoded = label_encoder.transform(y_test)

    # Assume the features have the shape (your_feature_shape,)
    input_shape = X_train.shape[1:]

    # Create a simple model
    input_tensor = Input(shape=input_shape)
    x = Dense(256, activation='relu')(input_tensor)
    predictions = Dense(len(labels), activation='softmax')(x)

    model = Model(inputs=input_tensor, outputs=predictions)

    # Compile the model
    model.compile(optimizer='adam',  loss='sparse_categorical_crossentropy',  metrics=['accuracy'])

    # Train the model
    history = model.fit(X_train, y_train_encoded, epochs=10, batch_size=32, validation_split=0.1)

# Evaluate the model on the test set
    loss, accuracy = model.evaluate(X_test, y_test_encoded)
    print(f"Test Accuracy: {accuracy * 100:.2f}%")

    train_accuracy = history.history['accuracy'][-1]
    print(f"Train Accuracy: {train_accuracy * 100:.2f}%")


main()

# Accurate Inception v3

import os
import numpy as np
import tensorflow as tf
```

```
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Flatten, Dropout
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder

# Load features and labels from all .npy files in a folder
def load_data(folder_path):
    data = []
    labels = []

    for file_name in os.listdir(folder_path):
        if file_name.endswith('.npy'):
            features = np.load(os.path.join(folder_path, file_name))
            label = folder_path.split('/')[-1]  # Assumes folder name is the label
            data.append(features)
            labels.extend([label] * features.shape[0])

    data = np.concatenate(data, axis=0)
    return data, labels

# Define Inception model
def create_inception_model(input_shape):
    model = Sequential()
    model.add(Flatten(input_shape=input_shape))
    model.add(Dense(256, activation='relu'))
    model.add(Dropout(0.5))
    model.add(Dense(num_classes, activation='softmax'))
    return model

# Load data from four folders
folder_paths = [
"C:/Users/HP/Desktop/Taboo/Final Year Project/Final-Year-Project/Dataset/masked/COVID-
19_Radiography_Dataset/ExtractedFeatures/Bacterial",
"C:/Users/HP/Desktop/Taboo/Final Year Project/Final-Year-Project/Dataset/masked/COVID-
19_Radiography_Dataset/ExtractedFeatures/Covid",
"C:/Users/HP/Desktop/Taboo/Final Year Project/Final-Year-Project/Dataset/masked/COVID-
19_Radiography_Dataset/ExtractedFeatures/Healthy",
"C:/Users/HP/Desktop/Taboo/Final Year Project/Final-Year-Project/Dataset/masked/COVID-
19_Radiography_Dataset/ExtractedFeatures/Viral"
]

all_data = []
all_labels = []

for folder_path in folder_paths:
    folder_data, folder_labels = load_data(folder_path)
    all_data.append(folder_data)
    all_labels.extend(folder_labels)

data = np.concatenate(all_data, axis=0)

# Encode labels
label_encoder = LabelEncoder()
encoded_labels = label_encoder.fit_transform(all_labels)
num_classes = len(label_encoder.classes_)
```

```
# Split data into train and test sets
X_train, X_test, y_train, y_test = train_test_split(data, encoded_labels, test_size=0.2,
random_state=42)

# Create and compile the model
model = create_inception_model(input_shape=data.shape[1:])
model.compile(optimizer='adam', loss='sparse_categorical_crossentropy', metrics=['accuracy'])

# Train the model
model.fit(X_train, y_train, epochs=10, batch_size=32, validation_split=0.2)

# Evaluate the model on the test set
accuracy = model.evaluate(X_test, y_test)[1]
print(f'Test accuracy: {accuracy*100}')

# Optionally, save the model for later use
model.save('inception_model.h5')

import tensorflow as tf
from tensorflow.keras import layers, models

# Define the AlexNet model architecture
def alexnet_model(input_shape=(227, 227, 3), num_classes=1000):
    model = models.Sequential()

    # Layer 1
    model.add(layers.Conv2D(96, (11, 11), strides=(4, 4), activation='relu', input_shape=input_shape))
    model.add(layers.BatchNormalization())
    model.add(layers.MaxPooling2D((3, 3), strides=(2, 2)))

    # Layer 2
    model.add(layers.Conv2D(256, (5, 5), padding='same', activation='relu'))
    model.add(layers.BatchNormalization())
    model.add(layers.MaxPooling2D((3, 3), strides=(2, 2)))

    # Layer 3
    model.add(layers.Conv2D(384, (3, 3), padding='same', activation='relu'))

    # Layer 4
    model.add(layers.Conv2D(384, (3, 3), padding='same', activation='relu'))

    # Layer 5
    model.add(layers.Conv2D(256, (3, 3), padding='same', activation='relu'))
    model.add(layers.MaxPooling2D((3, 3), strides=(2, 2)))

    # Flatten and fully connected layers
    model.add(layers.Flatten())
    model.add(layers.Dense(4096, activation='relu'))
    model.add(layers.Dropout(0.5))
    model.add(layers.Dense(4096, activation='relu'))
    model.add(layers.Dropout(0.5))
    model.add(layers.Dense(num_classes, activation='softmax'))

    return model

# Create the AlexNet model
```

```
model = alexnet_model()

# Display the model summary
model.summary()

import tensorflow as tf
from tensorflow.keras import layers, models

def build_adeco_cnn(input_shape):
    # Define convolutional layers
    model = tf.keras.Sequential([
        layers.Conv2D(32, kernel_size=(3, 3), activation='relu', input_shape=input_shape),
        layers.MaxPooling2D(pool_size=(2, 2)),
        layers.Conv2D(64, kernel_size=(3, 3), activation='relu'),
        layers.MaxPooling2D(pool_size=(2, 2)),
        layers.Conv2D(128, kernel_size=(3, 3), activation='relu'),
        layers.MaxPooling2D(pool_size=(2, 2)),
        layers.Flatten(),

        # Flatten and connect to dense layers
        layers.Dense(256, activation='relu'),
        layers.Dropout(0.5),
        layers.Dense(1, activation='sigmoid')  # Sigmoid for binary classification
    ])

    model.compile(optimizer='adam',
                  loss='binary_crossentropy',
                  metrics=['accuracy'])
    return model

# Assuming input image dimensions are 120x120 pixels with 3 color channels
input_shape = (120, 120, 3)

# Create the ADECO-CNN model
adeco_cnn_model = build_adeco_cnn(input_shape)

# Display the model architecture
adeco_cnn_model.summary()

import os
import numpy as np
import tensorflow as tf
from tensorflow.keras import layers, models
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder

# Load features and labels from all .npy files in a folder
def load_data(folder_path):
    data = []
    labels = []

    for file_name in os.listdir(folder_path):
        if file_name.endswith('.npy'):
            features = np.load(os.path.join(folder_path, file_name))
            label = folder_path.split('/')[-1]  # Assumes folder name is the label
            data.append(features)
```

```
            labels.extend([label] * features.shape[0])

    data = np.concatenate(data, axis=0)
    return data, labels

# Define ADECO-CNN model architecture
def build_adeco_cnn(input_shape, num_classes):
    model = tf.keras.Sequential([
        layers.Conv2D(32, kernel_size=(3, 3), activation='relu', input_shape=input_shape),
        layers.MaxPooling2D(pool_size=(2, 2)),
        layers.Conv2D(64, kernel_size=(3, 3), activation='relu'),
        layers.MaxPooling2D(pool_size=(2, 2)),
        layers.Conv2D(128, kernel_size=(3, 3), activation='relu'),
        layers.MaxPooling2D(pool_size=(2, 2)),
        layers.Flatten(),
        layers.Dense(256, activation='relu'),
        layers.Dropout(0.5),
        layers.Dense(num_classes,  activation='softmax')
    ])
    return model

folder_paths = [
    "C:/Users/HP/Desktop/Taboo/Final Year Project/Final-Year-Project/Dataset/masked/COVID-
19_Radiography_Dataset/ExtractedFeatures/Bacterial",
    "C:/Users/HP/Desktop/Taboo/Final Year Project/Final-Year-Project/Dataset/masked/COVID-
19_Radiography_Dataset/ExtractedFeatures/Covid",
    "C:/Users/HP/Desktop/Taboo/Final Year Project/Final-Year-Project/Dataset/masked/COVID-
19_Radiography_Dataset/ExtractedFeatures/Healthy",
    "C:/Users/HP/Desktop/Taboo/Final Year Project/Final-Year-Project/Dataset/masked/COVID-
19_Radiography_Dataset/ExtractedFeatures/Viral"
]
all_data = []
all_labels = []

for folder_path in folder_paths:
    folder_data, folder_labels = load_data(folder_path)
    all_data.append(folder_data)
    all_labels.extend(folder_labels)

data = np.concatenate(all_data, axis=0)

# Encode labels
label_encoder = LabelEncoder()
encoded_labels = label_encoder.fit_transform(all_labels)
num_classes = len(label_encoder.classes_)

# Split data into train and test sets
X_train, X_test, y_train, y_test = train_test_split(data, encoded_labels, test_size=0.2,
random_state=42)

# Reshape the data to represent images
input_shape = (32, 32, 1)  # Assuming grayscale images with dimensions 32x32
X_train = X_train.reshape(-1, 32, 32, 1)
X_test = X_test.reshape(-1, 32, 32, 1)

# Create and compile the ADECO-CNN model
```

```
model = build_adeco_cnn(input_shape, num_classes)
model.compile(optimizer='adam',  loss='sparse_categorical_crossentropy',  metrics=['accuracy'])

# Train the model
model.fit(X_train, y_train, epochs=10, batch_size=32, validation_split=0.2)

# Evaluate the model on the test set
accuracy = model.evaluate(X_test, y_test)[1]
print(f'Test accuracy: {accuracy*100}')

# Optionally, save the model for later use
model.save('adeco_cnn_model.h5')

from keras.applications import ResNet50
from keras.layers import Input
from keras.models import Model
from keras import models
from keras.layers import GlobalAveragePooling2D, Dense
# Assuming the original images are 32x32 grayscale
input_shape = (32, 32, 3)

# Create the ResNet50 model with the correct input shape and pre-trained weights
base_model = ResNet50(weights='imagenet', include_top=False, input_shape=input_shape)

# Add your custom layers on top of the base model
x = base_model.output
x = GlobalAveragePooling2D()(x)
x = Dense(1024, activation='relu')(x)
predictions = Dense(num_classes, activation='softmax')(x)

# Combine the base model with your custom layers
model = Model(inputs=base_model.input, outputs=predictions)

# Compile the model
model.compile(optimizer='adam',  loss='categorical_crossentropy',  metrics=['accuracy'])

# Print model summary
model.summary()

from keras.applications import ResNet50
from keras.layers import Input
from keras.models import Model
from keras import models
from keras.layers import GlobalAveragePooling2D, Dense
# Assuming the original images are 32x32 grayscale
input_shape = (32, 32, 3)

# Create the ResNet50 model with the correct input shape and pre-trained weights
base_model = ResNet50(weights='imagenet', include_top=False, input_shape=input_shape)

# Add your custom layers on top of the base model
x = base_model.output
x = GlobalAveragePooling2D()(x)
x = Dense(1024, activation='relu')(x)
predictions = Dense(num_classes, activation='softmax')(x)
```

```
# Combine the base model with your custom layers
model = Model(inputs=base_model.input, outputs=predictions)

# Compile the model
model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

# Print model summary
model.summary()
from keras.applications import vgg16, densenet, xception, nasnet, efficientnet
from keras.models import load_model



densenet_model = densenet.DenseNet121(weights='imagenet', include_top=True)
xception_model = xception.Xception(weights='imagenet', include_top=True)
nasnet_model = nasnet.NASNetLarge(weights='imagenet', include_top=True)
efficientnet_model = efficientnet.EfficientNetB7(weights='imagenet', include_top=True)

from keras.models import load_model

# Load the models
loaded_densenet_model = load_model('densenet_model.h5')
loaded_xception_model = load_model('xception_model.h5')
loaded_nasnet_model = load_model('nasnet_model.h5')
loaded_efficientnet_model = load_model('efficientnet_model.h5')
print("DenseNet121 model summary:")
print(loaded_densenet_model.summary())



print("Xception model summary:")
print(loaded_xception_model.summary())

print("NASNetLarge model summary:")
print(loaded_nasnet_model.summary())
print("EfficientNetB7 model summary:")
print(loaded_efficientnet_model.summary())
# Split data into train and test sets
X_train, X_test, y_train, y_test = train_test_split(data.reshape(-1, 32, 32, 1), encoded_labels,
test_size=0.2, random_state=42)

# Convert grayscale images to RGB
X_train = np.repeat(X_train, 3, axis=-1)
X_test = np.repeat(X_test, 3, axis=-1)

# Reshape the data to represent RGB images
input_shape = (32, 32, 3)  # Assuming the original images are 32x32 RGB
X_train = X_train.reshape(-1, 32, 32, 3)
X_test = X_test.reshape(-1, 32, 32, 3)

# Create the VGG19 model with the correct input shape and pre-trained weights
base_model = VGG19(weights='imagenet', include_top=False, input_shape=input_shape)

# Add custom layers on top of the base model
x = base_model.output
x = layers.Flatten()(x)
```

```
x = layers.Dense(256, activation='relu')(x)
predictions = layers.Dense(num_classes, activation='softmax')(x)

# Combine the base model with the custom layers
model = models.Model(inputs=base_model.input, outputs=predictions)

# Compile the model
model.compile(optimizer='adam',  loss='sparse_categorical_crossentropy',  metrics=['accuracy'])

# Train the model
model.fit(X_train, y_train, epochs=10, batch_size=32, validation_split=0.2)

# Evaluate the model on the test set
accuracy = model.evaluate(X_test, y_test)[1]
print(f'Test accuracy: {(accuracy)*100}')

# Optionally, save the model for later use
model.save('vgg19_model.h5')

from tensorflow.keras.applications import DenseNet121

# Assuming the original images are 32x32 RGB
input_shape = (32, 32, 3)

# Create the DenseNet121 model with the correct input shape and pre-trained weights
base_model = DenseNet121(weights='imagenet', include_top=False, input_shape=input_shape)

# Add custom layers on top of the base model
x = base_model.output
x = layers.GlobalAveragePooling2D()(x)  # Change from Flatten to GlobalAveragePooling2D for
DenseNet
x = layers.Dense(256, activation='relu')(x)
predictions = layers.Dense(num_classes, activation='softmax')(x)

# Combine the base model with the custom layers
model = models.Model(inputs=base_model.input, outputs=predictions)

# Compile the model
model.compile(optimizer='adam',  loss='sparse_categorical_crossentropy',  metrics=['accuracy'])

# Train the model
model.fit(X_train, y_train, epochs=10, batch_size=32, validation_split=0.2)

# Evaluate the model on the test set
accuracy = model.evaluate(X_test, y_test)[1]
print(f'Test accuracy: {(accuracy)*100}')

# Optionally, save the model for later use
model.save('densenet121_model.h5')

from tensorflow.keras.applications import EfficientNetB0

# Assuming the original images are 32x32 RGB
input_shape = (32, 32, 3)

# Create the EfficientNetB0 model with the correct input shape and pre-trained weights
```

```
base_model = EfficientNetB0(weights='imagenet', include_top=False, input_shape=input_shape)

# Add custom layers on top of the base model
x = base_model.output
x = layers.GlobalAveragePooling2D()(x)  # Change from Flatten to GlobalAveragePooling2D for
EfficientNet
x = layers.Dense(256, activation='relu')(x)
predictions = layers.Dense(num_classes, activation='softmax')(x)

# Combine the base model with the custom layers
model = models.Model(inputs=base_model.input, outputs=predictions)

# Compile the model
model.compile(optimizer='adam',  loss='sparse_categorical_crossentropy',  metrics=['accuracy'])

# Train the model
model.fit(X_train, y_train, epochs=10, batch_size=32, validation_split=0.2)

# Evaluate the model on the test set
accuracy = model.evaluate(X_test, y_test)[1]
print(f'Test accuracy: {(accuracy)*100}')

# Optionally, save the model for later use
model.save('efficientnetb0_model.h5')

XAI.ipynb
import cv2
import numpy as np
import matplotlib.pyplot as plt

def apply_clahe_to_single_image(input_image, clip_limit=2.0, grid_size=(8, 8)):
    # Convert the image to LAB color space
    lab = cv2.cvtColor(input_image, cv2.COLOR_BGR2LAB)

    # Split the LAB image into L, A, and B channels
    l, a, b = cv2.split(lab)

    # Apply CLAHE to the L channel
    clahe = cv2.createCLAHE(clipLimit=clip_limit, tileGridSize=grid_size)
    cl = clahe.apply(l)

    # Merge the enhanced L channel with the original A and B channels
    enhanced_lab = cv2.merge((cl, a, b))

    # Convert the LAB image back to BGR color space
    enhanced_img = cv2.cvtColor(enhanced_lab, cv2.COLOR_LAB2BGR)

    return enhanced_img

def calculate_enhancement_percentage(original_hist, enhanced_hist):
    original_bins = np.arange(256)
    enhanced_bins = np.arange(256)

    original_total_pixels = np.sum(original_hist)
    enhanced_total_pixels = np.sum(enhanced_hist)
```

```
    original_cumulative_sum = np.cumsum(original_hist)
    enhanced_cumulative_sum = np.cumsum(enhanced_hist)

    original_cdf_normalized = original_cumulative_sum / original_total_pixels
    enhanced_cdf_normalized = enhanced_cumulative_sum / enhanced_total_pixels

    diff_cdf = np.abs(original_cdf_normalized - enhanced_cdf_normalized)

    max_diff = np.max(diff_cdf)

    enhancement_percentage = (1 - max_diff) * 100

    return enhancement_percentage


# Set the input image path
input_image_path = "./Normal-34.png"
# Read the input image
input_image = cv2.imread(input_image_path)

# Apply CLAHE to the single image
enhanced_image = apply_clahe_to_single_image(input_image, clip_limit=2.0, grid_size=(8, 8))

# Convert images to grayscale for histogram calculation
input_gray = cv2.cvtColor(input_image, cv2.COLOR_BGR2GRAY)
enhanced_gray = cv2.cvtColor(enhanced_image, cv2.COLOR_BGR2GRAY)

# Calculate histograms
original_hist = cv2.calcHist([input_gray], [0], None, [256], [0, 256])
enhanced_hist = cv2.calcHist([enhanced_gray], [0], None, [256], [0, 256])

# Calculate enhancement percentage
enhancement_percentage = calculate_enhancement_percentage(original_hist, enhanced_hist)

# Display the original and enhanced images
cv2.imshow("Original Image", input_image)
cv2.imshow("Enhanced Image", enhanced_image)
cv2.waitKey(0)
cv2.destroyAllWindows()     model.add(Flatten())
    model.add(Dropout(0.5))
    model.add(Dense(num_classes, activation='softmax'))
    return model



for folder_path in folder_paths:
    folder_data, folder_labels = load_data(folder_path)
    all_data.append(folder_data)
    all_labels.extend(folder_labels)

data = np.concatenate(all_data, axis=0)


# Encode labels
label_encoder = LabelEncoder()
encoded_labels = label_encoder.fit_transform(all_labels)
```

```
num_classes = len(label_encoder.classes_)


# Split data into train and test sets
X_train, X_test, y_train, y_test = train_test_split(data, encoded_labels, test_size=0.2,
random_state=42)

# Create and compile the model
input_shape = X_train.shape[1:]  # Assuming X_train has shape (number_of_samples, feature_dim)
VGGmodel = create_vgg16_model(input_shape=input_shape, num_classes=num_classes)
VGGmodel.compile(optimizer='adam', loss='sparse_categorical_crossentropy', metrics=['accuracy'])


VGGmodel.fit(X_train, y_train, epochs=10, batch_size=32, validation_split=0.2)

explainer = shap.Explainer(VGGmodel, masker=shap.maskers.Independent(X_train))
shap_values = explainer.shap_values(X_test)

accuracy = VGGmodel.evaluate(X_test, y_test)[1]
print(f'Test accuracy: {accuracy}')

shap.summary_plot(shap_values, X_test)

import os
import numpy as np
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Flatten, Dropout
from transformers.utils import GENERATION_CONFIG_NAME
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
import shap


# Load features and labels from all .npy files in a folder
def load_data(folder_path):
    data = []
    labels = []

    for file_name in os.listdir(folder_path):
        if file_name.endswith('.npy'):
            features = np.load(os.path.join(folder_path, file_name))
            label = folder_path.split(os.path.sep)[-1]  # Assumes folder name is the label
            data.append(features)
            labels.extend([label] * features.shape[0])

    data = np.concatenate(data, axis=0)
    return data, labels

folder_paths = [
    "C:/Users/HP/Desktop/Taboo/Final Year Project/Final-Year-Project/Dataset/masked/COVID-
19_Radiography_Dataset/ExtractedFeatures/Bacterial",
    "C:/Users/HP/Desktop/Taboo/Final Year Project/Final-Year-Project/Dataset/masked/COVID-
19_Radiography_Dataset/ExtractedFeatures/Covid",
    "C:/Users/HP/Desktop/Taboo/Final Year Project/Final-Year-Project/Dataset/masked/COVID-
19_Radiography_Dataset/ExtractedFeatures/Healthy",
```

```
    "C:/Users/HP/Desktop/Taboo/Final Year Project/Final-Year-Project/Dataset/masked/COVID-19_Radiography_Dataset/ExtractedFeatures/Viral"
]
all_data = []
all_labels = []

# Split data into train and test sets
X_train, X_test, y_train, y_test = train_test_split(data, encoded_labels, test_size=0.2, random_state=42)

# Create and compile the model
input_shape = X_train.shape[1:]  # Assuming X_train has shape (number_of_samples, feature_dim)
incmodel = create_inception_model(input_shape=input_shape)
incmodel.compile(optimizer='adam', loss='sparse_categorical_crossentropy', metrics=['accuracy'])

incmodel.fit(X_train, y_train, epochs=10, batch_size=32, validation_split=0.2)

explainer = shap.Explainer(incmodel, masker=shap.maskers.Independent(X_train))
shap_values = explainer.shap_values(X_test)

accuracy = incmodel.evaluate(X_test, y_test)[1]
print(f'Test accuracy: {accuracy}')

shap.summary_plot(shap_values, X_test)

shap.initjs()

print(f"Current label Shown: {encoded_labels}")

shap.force_plot(
base_value=explainer.expected_value[encoded_labels[0]],
    shap_values=shap_values[encoded_labels[0]],
    features=data[0:50, :],
)
```

Main.py

```
import streamlit as st
import cv2
import numpy as np
import tensorflow as tf
import matplotlib.pyplot as plt
from tensorflow.keras.models import Model
from tensorflow.keras.layers import Conv2D, MaxPooling2D, UpSampling2D, Dropout, concatenate, Conv2DTranspose, Input
from tensorflow.keras.layers import Multiply, Add
from tensorflow.keras.metrics import MeanIoU
from tensorflow.keras.models import Model
from tensorflow.keras.layers import Conv2D, MaxPooling2D, UpSampling2D, Dropout, concatenate, Conv2DTranspose, Input, Dense, Flatten, Dropout
from tensorflow.keras.models import Sequential
from sklearn.preprocessing import LabelEncoder

def apply_clahe_to_single_image(input_image, clip_limit=2.0, grid_size=(8, 8)):
    lab = cv2.cvtColor(input_image, cv2.COLOR_BGR2LAB)
```

```
    l, a, b = cv2.split(lab)
    clahe = cv2.createCLAHE(clipLimit=clip_limit, tileGridSize=grid_size)
    cl = clahe.apply(l)
    enhanced_lab = cv2.merge((cl, a, b))
    enhanced_img = cv2.cvtColor(enhanced_lab, cv2.COLOR_LAB2BGR)
    return enhanced_img

def load_image(image_path, SIZE):
    image = cv2.imread(image_path)
    image = cv2.resize(image, (SIZE, SIZE))
    image = image.astype(np.float32) / 255.0
    return image


def load_mask(mask_path, SIZE):
    mask = cv2.imread(mask_path, cv2.IMREAD_GRAYSCALE)
    mask = cv2.resize(mask, (SIZE, SIZE))
    mask = mask.astype(np.float32) / 255.0
    mask = np.expand_dims(mask, axis=-1)
    return mask


def show_image_with_mask(image, mask, title=None):
    plt.imshow(image)
    plt.imshow(mask, cmap='gray', alpha=0.2)  # Use 'gray' colormap
    if title is not None:
        plt.title(title)
    plt.axis('off')


def conv_block(inputs=None, n_filters=32, dropout_prob=0, max_pooling=True):
    conv = Conv2D(n_filters, 3, activation='relu', padding='same',
kernel_initializer='he_normal')(inputs)
    conv = Conv2D(n_filters, 3, activation='relu', padding='same', kernel_initializer='he_normal')(conv)


    if dropout_prob > 0:
        conv = Dropout(dropout_prob)(conv)


    if max_pooling:
        next_layer = MaxPooling2D()(conv)
    else:
        next_layer = conv


    skip_connection = conv


    return next_layer, skip_connection


def upsampling_block(expansive_input, contractive_input, n_filters=32):
    up = Conv2DTranspose(n_filters, 3, strides=(2, 2), padding='same')(expansive_input)

    merge = concatenate([up, contractive_input], axis=3)
```

```
    conv = Conv2D(n_filters, 3, activation='relu', padding='same',
kernel_initializer='he_normal')(merge)
    conv = Conv2D(n_filters, 3, activation='relu', padding='same', kernel_initializer='he_normal')(conv)

    return conv


def unet_model(input_size=(96, 128, 3), n_filters=32, n_classes=1):
    inputs = Input(input_size)


    cblock1 = conv_block(inputs, n_filters)
    cblock2 = conv_block(cblock1[0], n_filters * 2)
    cblock3 = conv_block(cblock2[0], n_filters * 4)
    cblock4 = conv_block(cblock3[0], n_filters * 8, dropout_prob=0.3)


    cblock5 = conv_block(cblock4[0], n_filters*16, dropout_prob=0.3, max_pooling=False)


    ublock6 = upsampling_block(cblock5[0], cblock4[1],  n_filters * 8)


    ublock7 = upsampling_block(ublock6, cblock3[1],  n_filters * 4)
    ublock8 = upsampling_block(ublock7, cblock2[1],  n_filters * 2)
    ublock9 = upsampling_block(ublock8, cblock1[1],  n_filters)


    conv9 = Conv2D(n_filters,
                3,
                activation='relu',
                padding='same',
                kernel_initializer='he_normal')(ublock9)


    conv10 = Conv2D(n_classes, 1, padding='same', activation='sigmoid')(conv9)


    model = tf.keras.Model(inputs=inputs, outputs=conv10)


    return model

def load_classification_model():
    inceptionv3_model_path = "C:/Users/HP/Desktop/Taboo/Final Year Project/Final-Year-
Project/Semester VIII/inception_model.h5"  # Replace with your actual path
    inceptionv3_model = tf.keras.models.load_model(inceptionv3_model_path)

    chosen_layer_name = 'dense_40'
    num_classes = 4

    inception_base_model = Model(inputs=inceptionv3_model.input,
outputs=inceptionv3_model.get_layer(chosen_layer_name).output)

    classification_model = Sequential()
    classification_model.add(inception_base_model)
```

```
    classification_model.add(Dense(256, activation='relu'))
    classification_model.add(Dropout(0.5))
    classification_model.add(Dense(num_classes, activation='softmax'))

    classification_model.compile(optimizer='adam', loss='sparse_categorical_crossentropy',
metrics=['accuracy'])

    return classification_model


from sklearn.decomposition import PCA

def extract_features(image):

    inceptionv3_model = tf.keras.applications.InceptionV3(include_top=False, weights='imagenet',
input_shape=(299,299,3))


    preprocessed_image = tf.keras.applications.inception_v3.preprocess_input(image)


    features = inceptionv3_model.predict(preprocessed_image[np.newaxis, ...])


    features = features.flatten()


    features = features[:1024]

    return features

unet = unet_model((256, 256, 3))
unet.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy', MeanIoU(2)])


def main():
    st.title("Segmentation and Classification")
    uploaded_image = st.file_uploader("Upload an enhanced lung image", type=["jpg", "png", "jpeg"])
    uploaded_mask = st.file_uploader("Upload the corresponding mask", type=["jpg", "png", "jpeg"])
    if uploaded_mask is not None:

        mask_bytes = np.asarray(bytearray(uploaded_mask.read()), dtype=np.uint8)
        mask_image = cv2.imdecode(mask_bytes, 0)

        mask_resized = cv2.resize(mask_image, (256, 256))
        mask_resized = mask_resized.astype(np.float32) / 255.0

    if uploaded_image is not None:

      file_bytes = np.asarray(bytearray(uploaded_image.read()), dtype=np.uint8)
      enhanced_image = cv2.imdecode(file_bytes, 1)

main()
```

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Greetings from Shenbagarajan Anantharajan.

In this connection, we would like to submit our research article for the possible inclusion in your esteemed journal. This research work carries out for the identification of Pneumonia using ML and DL concepts. The proposed method achieved greater efficiency with other existing methods.

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