A

Project Report

on

CHEST X-RAY REPORT GENERATOR

submitted for partial fulfillment for the award of

BACHELOR OF TECHNOLOGY DEGREE

in

Computer Science

By

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May 2024

DECLARATION

We hereby declare that this submission is our work and that, to the best of our knowledge and belief, it contains no material previously published or written by another person nor material which to a substantial extent has been accepted for the award of any other degree or diploma of the university or other institute of higher learning, except where due acknowledgment has been made in the text.

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This is to certify that the Project Report entitled "**Chest X-Ray Report Generator"** which is submitted by **Sujal Gupta, Vikas Yadav and Anmol Ratan** in partial fulfillment of the requirement for the award of degree B. Tech. in the Department of Computer Science of Dr A.P.J. Abdul Kalam Technical University, Lucknow is a record of the candidate's own work carried out by him under my supervision. The matter embodied in this report is original and has not been submitted for the award of any other degree.

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Finally, we acknowledge our friends for their contribution to the completion of the project.

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ABSTRACT

Medical Imaging is indispensable for clinical analysis and the visualization of organ functions within the human body, especially chest. Techniques like X-ray play a pivotal role in diagnosing and treating various conditions. The unprecedented demand for x ray reports during the COVID-19 pandemic highlighted the critical need for swift and accurate diagnostics, particularly concerning chest-related ailments. Even in the post-pandemic era, increased awareness has led to a surge in medical imaging demands, underscoring the necessity for efficient, accurate and automatic processes of generating reports. The traditional method of generating radiological reports relies heavily on the expertise of radiologists. While experienced professionals can provide accurate interpretations, the process is time-intensive, requiring an average of 10 minutes or more per report. In crowded healthcare settings or regions with limited resources, this approach proves impractical and potentially problematic.

This introduces an intuitive mobile application that streamlines the traditional chest X-ray report generation process for users by incorporating a machine learning (ML) model in an android app. The app seamlessly uses machine learning (ML) model in the form of encoder decoder mechanism, to provide comprehensible reports in layman's language in the android mobile application. The application enables users to capture chest X-ray images using their smartphone cameras, facilitating personalized reports based on the provided x ray image by the user.

The user-friendly process begins with the user capturing the image of the chest X-ray through the app's camera interface or directly selecting the image file from the file, the image is then processed through the ML model, utilizing the encoder decoder mechanism thus generating reports with commonly used words and phrases that are easily understood by individuals having a non-medical background. The generated report not only highlights the presence or absence of chest-related abnormalities but also conveys the information in a clear and accessible manner. By providing actionable insights in layman's language, users can promptly understand the results and make informed decisions about their health. In response to the heightened awareness of chest diseases post-COVID-19, this app serves as a crucial tool for individuals to actively know their chest health. The feature of capturing the image through your own mobile camera of your chest x ray simplifies the process, making chest X-ray analysis accessible to users without specialized medical knowledge.

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LIST OF ABBREVIATIONS

Acronym	**Definition**
CNN	Convolutional Neural Network
DL	Deep Learning
AI	Artificial Intelligence
ML	Machine Learning
IDE	Integrated Development Environment
TFLite	TensorFlow Lite
GUI	Graphical User Interface
API	Application Programming Interface
GPU	Graphics Processing Unit
RNN	Recurrent Neural Network
LR	Logistic Regression
CAM	Chained Context Aggregation Module.

CHAPTER 1

INTRODUCTION

1.1 Introduction

In the medical field there is a term called Medical Imaging, it is the process of creating visual representations of the interior of the body for clinical analysis as well as visual representation of the function of organs or tissues. It is one of the most significant and widely used methods for diagnosis and treatment. Some of the significant examples of medical imaging are X- Ray, MRI (Magnetic Resonance Imaging) etc. During the pandemic times (Covid-19) we saw that there was surge in the demands of medical imaging and Nowadays after the post pandemic (Covid19) we have seen that people have become more conscious towards the diseases, especially chest related diseases. Detailed information generated from medical images is necessary for diagnosing illnesses or tracking patients' progress. However, every image requires a radiologist to carefully examine and write a full-text report to describe the findings. Diagnosing medical images requires an appropriate amount of experience from the radiologists to develop more confident and accurate reports. Furthermore, a more glaring issue is the amount of time it takes the radiologist to write a full-text report. It would take on average 10 min or more based on the radiologist's degree of experience, so this would prove very time consuming when considering the number of cases, a radiologist should investigate per day, and in crowded hospitals, regions, and cities, this would be problematic. Also, for less-experienced radiologists and pathologists, especially those working in the rural area where the quality of healthcare is relatively low, writing medical-imaging reports is demanding. For instance, to correctly read a chest x-ray image, the following skills are needed like thorough knowledge of the normal anatomy of the thorax, the basic physiology of chest diseases; skills of analyzing the radiograph through a fixed pattern probability of evaluating the evolution over time knowledge of clinical presentation and history knowledge of the correlation with other diagnostic results (laboratory results, electrocardiogram, and respiratory function tests). identifying symptoms and recommending appropriate treatment options in real time. So, for this we provide an intuitive mobile application that streamlines the traditional chest X-ray report generation process for users by incorporating a machine learning (ML) model in an android app. The app seamlessly uses machine learning (ML) model in the form of encoder decoder mechanism, to provide comprehensible reports in layman's language in the android mobile application. The application enables users to capture chest X-ray images using their smartphone cameras, facilitating personalized reports based on the provided x ray image by the user.

The user-friendly process begins with the user capturing the image of the chest X-ray through the app's camera interface or directly selecting the image from the file, the image is then processed through the ML model, utilizing the encoder decoder mechanism thus generating reports with commonly used words and phrases that are easily understood by individuals having a non-medical background.

The generated report not only highlights the presence or absence of chest-related abnormalities but also conveys the information in a clear and accessible manner. By providing actionable insights in layman's language, users can promptly understand the results and make informed decisions about their health.

In response to the heightened awareness of chest diseases post-COVID-19, this app serves as a crucial tool for individuals to actively know their chest health. The feature of capturing the image through your own mobile camera of your chest x ray simplifies the process, making chest X-ray analysis accessible to users without specialized medical knowledge. This innovative solution not only addresses the increased consciousness about chest health but also promotes early detection and informed health management. Medical Imaging is indispensable for clinical analysis and the visualization of organ functions within the human body, especially chest. Techniques like X-ray play a pivotal role in diagnosing and treating various conditions. The unprecedented demand for x ray reports during the COVID-19 pandemic highlighted the critical need for swift and accurate diagnostics, particularly concerning chest-related ailments. Even in the post-pandemic era, increased awareness has led to a surge in medical imaging demands, underscoring the necessity for efficient, accurate and automatic processes of generating reports.

1.2 Project Category

Our project falls within the field of generating reports by the usage of chest x ray images, which utilizes Machine Learning to generate precise reports by analyzing the chest x ray images provided by the user. Specifically, it intersects with the broader domain of HealthNet, where machine learning and techniques are employed to enhance the capability and efficiency of our current healthcare system. Our focus lies in automating the process of report generation, which is a critical aspect of Medical Imaging and reports generation to identify the irregularities in the x-rays. Instead of relying solely on human observation, we leverage computational powers and sophisticated algorithms to analyze the different parts of chest x-ray image and match for the irregularities. By analyzing the imagery provided by the user of its x-ray (chest x-ray), we can swiftly generate the report and identify any diseases or problems before they create any serious implications.

The significance of our project extends beyond technological innovation rather it has become the need our current healthcare system (and even more post covid-19). People have become increasingly heath conscious. (especially about their chest diseases). This app will act as the vantage platform for people to generate the report of their chest x- rays just by clicking the image through their Smartphone. Using our system, we enable people to proactively check the reports of their x rays and see any irregularities, thus enabling them to find any early diseases and even any further complications in their chest x-rays.

1.3 Objectives

Our main objectives are:

- Develop a user-friendly android app, allowing users to effortlessly capture images of chest X-ray using their camera of your mobile phone.
- Image Processing with ML Models: Implement encoder decoder mechanism for image analysis, enabling the extraction of relevant information from chest X-ray images.
- Layman-Friendly Reports: Using global vectors (glove.840B300d) in language generation for reports this converts the extracted information into commonly used words and phrases, ensuring reports are comprehensible to users without a medical background.
- Common chest Disease Detection and Identification based on x ray images: Implement machine learning for disease detection within chest X-ray images, providing accurate and reliable information about the presence or absence of abnormalities in the provided x-ray.
- Accessible Reporting and security: Develop a reporting system that conveys analysis results in layman's language, emphasizing clarity and ease of understanding for users.
- Real-Time Analysis: To enable real-time processing and reporting, allowing users to receive immediate reports on their chest X-ray images.

These objectives converge to drive our mission of leveraging technology to revolutionize healthcare system and medical imaging specifically to ensure sustainable agriculture and food security for generations to come.

1.4 Structure of the Report

The structure of the project report follows a systematic approach beginning with Chapter 1, which introduces the project, its category, objectives, and outlines the structure of the report itself. Chapter 2 delves into a comprehensive literature review, identifying research gaps and formulating the problem statement. Following this, Chapter 3 presents the proposed system along with its unique features. Moving forward, Chapter 4 focuses on requirement analysis and system specifications, including feasibility studies, software requirement specifications, and system design. Chapter 5 discusses the implementation phase, detailing tools, technologies, and dataset descriptions. Chapter 6 covers testing techniques and maintenance procedures, ensuring the system's reliability and sustainability. Chapter 7 presents the results and discussions, showcasing performance evaluations, key findings, and presentation of results through charts, graphs, and tables. Finally, Chapter 8 concludes the report, summarizing the findings, discussing future scopes, and providing closure. The report adheres to IEEE format for references, ensuring academic integrity and credibility throughout. This structured approach ensures clarity, coherence, and comprehensiveness in presenting the project's development and evaluation process.

CHAPTER 2

LITERATURE RIVIEW

2.1 Literature Review

The author of this study report talked about how chest-based diseases are becoming more common every day and how delayed diagnosis and treatment negatively impacts us diseases like pneumonia is hard to detect and diagnose even. The diagnosis of pneumonia through chest radiography presents a significant challenge for radiologists due to the inherent complexities in interpreting subtle visual cues within X-ray images. This difficulty is compounded by the potential overlap of pneumonia manifestations with other thoracic pathologies, as well as the varied presentation of benign abnormalities. Addressing this need, recent advancements in deep learning have paved the way for the development of sophisticated artificial intelligence models capable of automating pneumonia detection from chest X-ray images. In their seminal work, the authors introduce ChexNet, a state-of-the-art convolutional neural network (CNN) comprising 121 layers. ChexNet demonstrates remarkable proficiency in pneumonia detection, surpassing the performance levels typically achieved by practicing radiologists. The model leverages a vast repository of chest X-ray data provided by the ChestX-ray14 dataset, containing over 100,000 meticulously labeled images capturing various thoracic diseases, including pneumonia. [1]

Semantic segmentation, a fundamental task in computer vision, plays a crucial role in various applications such as automatic driving, medical imaging, and augmented reality. Modern techniques in semantic segmentation, particularly those based on Fully Convolutional Networks (FCN), have demonstrated optimal performance in this domain. However, FCN's continuous down sampling process often leads to the loss of spatial details, resulting in poor object delineation and the emergence of small spurious regions. This paradox between semantics and spatial details presents a significant challenge in achieving accurate segmentation results. To address these challenges, recent advancements have introduced innovative paradigms such as the Chained Context Aggregation Module (CAM). CAM utilizes Flow Guidance Connections to integrate multiple information flows in a series-parallel hybrid manner. Each flow consists of a shallow encoder-decoder architecture with suitable down sampling scales to capture contextual information. The serial and parallel flows within CAM, guided by Chained Connections, contain multiple encoder-decoder blocks, effectively increasing the receptive fields of output neurons and enhancing contextual and localization information. [2]

This research study discusses the task of generating natural language descriptions for images and their regions has garnered significant attention in the field of computer vision and natural language processing. In this context, the inter-modal correspondence between visual data and language plays a pivotal role. Existing approaches often rely on datasets containing images paired with sentence descriptions to learn these correspondences. A Multimodal Recurrent Neural Network (RNN) architecture is then proposed, utilizing the inferred alignments to generate novel descriptions of image regions. This architecture leverages the learned inter-modal correspondences to produce coherent and contextually relevant descriptions. [3]

Image caption generation, a task in the field of computer vision and natural language processing, involves generating natural language descriptions or captions for the content depicted in an image. Traditionally, a caption provides additional information that complements the image, although in this context, it refers to textual descriptions of images. These descriptions can be either concrete or conceptual, capturing the visual content of the image. The process of generating captions often involves the use of neural language models, particularly recurrent neural networks (RNNs) In summary, the literature on image caption generation highlights the importance of considering different approaches to incorporating image features into language models. These approaches can significantly impact the performance and capabilities of captioning systems, and further research is needed to explore their strengths and limitations comprehensively. [4]

Medical imaging plays a pivotal role in clinical practice, aiding in the diagnosis and treatment of various medical conditions. However, the process of report-writing associated with medical imaging can be error-prone for inexperienced physicians and time-consuming for experienced ones. To address these challenges, there is a growing interest in automatic generation of medical imaging reports. This task is multifaceted, presenting several challenges that need to be overcome. In conclusion, the automatic generation of medical imaging reports holds great promise in alleviating the burden associated with report-writing for physicians, both inexperienced and experienced. By leveraging advanced machine learning techniques, researchers aim to develop systems capable of producing accurate, comprehensive, and efficient medical imaging reports, ultimately enhancing patient care and clinical workflows. [5]

The communication between radiologists and general practitioners (GPs) plays a crucial role in the diagnosis and treatment of patients, particularly in the primary care setting where GPs heavily rely on radiology reports as their main source of imaging information. Unlike hospital-based clinicians, GPs lack direct contact with radiologists, making it challenging for them to discuss and clarify imaging issues. Additionally, radiologists often do not receive feedback from GPs regarding their preferences for radiology reports. In summary, this study seeks to address the gap in the literature regarding GPs' opinions of radiology reports by investigating their satisfaction levels, preferences, and perceptions. By understanding GPs' needs and preferences, healthcare providers can tailor radiology reports to better meet the requirements of primary care practitioners, ultimately improving communication and patient care outcomes. [6]

The introduction of the paper discusses the significance of medical imaging in hospitals and the importance of detailed reports for diagnosing illnesses and tracking patients' progress. However, writing full-text reports is time-consuming for radiologists, and many reports end with indecisive findings, leading to further tests. This motivates the research into deep learning models capable of automating report writing. Previous studies have explored automatic report generation using convolution-recurrent architectures (CNN-RNN) and attention-based models. The paper highlights the shift towards transformer-based models in natural language processing (NLP) research, motivating the investigation into using pre-trained transformers like GPT2 while conditioning them on visual features and semantic tags embeddings. In summary, the paper introduces CDGPT2, a conditioned transformer-based model for generating radiology reports from chest X-ray images. It discusses the training process, model architecture, and evaluation metrics, demonstrating its effectiveness in automating report writing and improving communication between radiologists and medical practitioners. [7]

The term "Smoothing Convolutional Factorizes Inception V3 Labels and Transformers for Image Feature Extraction into Text Segmentation" seems to describe a method or technique for extracting features from images and converting them into text segments.it appears that the proposed method involves using a combination of CNNs (possibly based on the Inception V3 architecture), factorization techniques, and transformer models to extract features from images and convert them into text segments or descriptions, possibly for tasks such as image captioning or object recognition. [8]

In this study, they proposed a model for classifying normal and abnormal sounds by extracting characteristics from abnormal heart sounds in which normal and symbolic murmurs appear. Heart sound data obtained through an electronic stethoscope are converted into mel-spectrogram images. The pre-trained Inception V3 model that carries out fine-tuning uses the mel-spectrogram image as input. Convolutional layers of fine-tuning completed Inception V3 models were used as feature extractors. A point-binary correlation analysis technique was used to select effective features for classification from the features extracted through the feature extractor. A crystal coefficient value, which is the square of the correlation coefficient value, is used for an accurate comparison between the features. We used an artificial neural network as a classifier in this experiment. Fine-tuned Inception V3 has an average accuracy of 87.7%. When 5-fold class validation is advanced by selecting the top 30 characteristics with high crystal coefficient values, the accuracy is 97.5%. These results can greatly assist physicians trying to detect a systolic murmur. [9]

Cardiovascular diseases (CVDs) are a significant global health concern, being the leading cause of death worldwide according to the World Health Organization (WHO). With approximately 17.9 million deaths attributed to CVDs in 2016, mainly from heart disease and stroke, the mortality rate continues to rise annually. In response to this, significant advancements have been made in cardiovascular research and practice over recent decades, aiming to enhance the diagnosis and treatment of cardiac diseases and ultimately reduce mortality rates associated with CVDs. The review aims to comprehensively cover the evolution of deep learning algorithms for cardiac image segmentation, encompassing various tasks such as LV, RV, and vessel segmentation. It categorizes influential publications in this field up to August 2019 based on specific methodologies employed. Additionally, the review includes discussions on the current research landscape, challenges, and potential future directions in cardiac image segmentation. Furthermore, it provides valuable resources for newcomers to the field, including summaries of public datasets and publicly available code, encouraging further contributions to this vital area of research. [10]

2.2 Research Gaps

Despite the significant progress in automated chest x–ray report generation using various machine learning and deep learning techniques outlined in the literature, several research gaps remain to be addressed. These gaps can be categorized as follows:

- Insights from studies such as [1] provide valuable guidance for the development of our project, particularly in understanding the efficacy of deep learning architectures and image feature extraction module in our project.
- Research by [2] offers valuable context regarding the segmentation targeted in previous studies, aiding in determining the scope of our research and identifying additional methods relevant to our report generation context.
- Practical challenges highlighted in studies like [3] inform our understanding of implementation challenges, guiding our strategies for addressing issues such as data availability and interpretability within the context of our project.
- Collaborative efforts provide the method to use the RNN, in studies such as [4] computer vision and NLP (natural language processing), shaping our approach to engaging stakeholders and ensuring the relevance and usability of our system.

- Lastly, insights from research on transformer-based machine learning and natural language processing may influence the ways and provide direction and shaping the way by our project, guiding our mitigation and adaptation strategies.

2.3 Problem Formulation

Medical Imaging is indispensable for clinical analysis and the visualization of organ functions within the human body, especially chest. Techniques like X-ray play a pivotal role in diagnosing and treating various conditions. The unprecedented demand for x ray reports during the COVID-19 pandemic highlighted the critical need for swift and accurate diagnostics, particularly concerning chest-related ailments. Even in the post-pandemic era, increased awareness has led to a surge in medical imaging demands, underscoring the necessity for efficient, accurate and automatic processes of generating reports.

The traditional method of generating radiological reports relies heavily on the expertise of radiologists. While experienced professionals can provide accurate interpretations, the process is time-intensive, requiring an average of 10 minutes or more per report. In crowded healthcare settings or regions with limited resources, this approach proves impractical and potentially problematic.

Moreover, inexperienced medical professionals, especially those in rural areas with lower healthcare standards, face challenges in interpreting complex chest X-ray images. A multitude of skills, including an in-depth understanding of thoracic anatomy, knowledge of chest disease physiology, and correlation with various diagnostic results, is necessary for accurate reporting. This patent addresses these challenges by proposing an innovative solution aimed at automating chest X-ray report generation by training the ML model. For this, we introduce an intuitive mobile application that streamlines the traditional chest X-ray report generation process for users by incorporating a machine learning (ML) model in an android app. The app seamlessly uses machine learning (ML) model in the form of encoder decoder mechanism, to provide comprehensible reports in layman's language in the android mobile application. The application enables users to capture chest X-ray images using their smartphone cameras, facilitating personalized reports based on the provided x ray image by the user. The user-friendly process begins with the user capturing the image of the chest X-ray through the app's camera interface or directly selecting the image file from the file, the image is then processed through the ML model, utilizing the encoder decoder mechanism thus generating reports with commonly used words and phrases that are easily understood by individuals having a non-medical background.

CHAPTER 3

PROPOSED SYSTEM

3.1 Proposed System

This proposed system (methodology) outlines the sequential steps involved in developing and deploying a Machine learning-based chest x-ray report generation system, from data collection to model inference. Each step plays a crucial role in ensuring the effectiveness and reliability of the system in real-world healthcare applications.

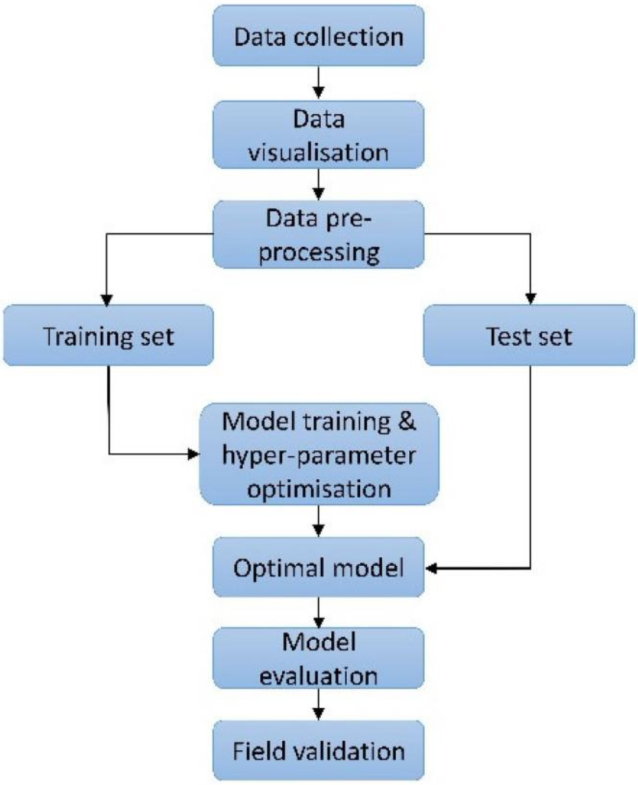


Fig 3.1 Proposed Methodology

a. **Gathering Datasets:** In this step, we collect a diverse set of images and their xml reports (for each report more than one image is possible) of chest x- rays containing chest-based diseases and irregularities. These datasets serve as the foundation for training and evaluating our encoder-decoder model. It's crucial to ensure that the datasets encompass a wide range of images and their reports to facilitate robust model development.

b. **Enhancing Data:** Once the datasets are collected, we pre-process the images to enhance their quality and relevance for the training process. This may involve techniques such as image normalization, resizing, and augmentation to standardize the data and increase its variability and data enhancement ensures that the model learns to generalize well to unseen images and variations in different conditions.

c. **Segmenting Data:** In this step, we segment the data which contains more than two images of chest x-rays from the background to get the uniformity across the report. further if the report has only one image, then the same image is added to maintain uniformity for report generation. We again create the uniformed pre-processed data without any errors containing id, image1, image2, report. This is further used in training and testing of the model.

d. **Model Development:** With pre-processed and uniformed datasets, we proceed to develop the model architecture. This involves designing a convolutional neural network (CNN) tailored for chest x-ray report generation. The architecture may consist of multiple convolutional layers (categorized into encoding and decoding layers predominantly) followed by pooling and optimization for fully connected layers to extract features from the input images using pre-trained ChexNet model. (Densenet-121 model which is fine tuned to detect the irregularities in the images of chest x-rays) and give output of sequence of strings as report.

e. **Training and Validation:** In this phase, the developed model is trained on the pre-processed datasets using Adam's optimization process for faster convergence of the data. Training involves feeding the model with labelled images and adjusting its parameters to minimize report generation errors. Validation datasets are used to evaluate the model's performance during training, ensuring that it generalizes well to unseen data and avoids over-fitting during the process.

Classification using CNN: Once the model is trained and validated, it is deployed for image features extraction and report generation using the CNN architecture. Input images are fed into the trained model, which then goes to the image feature extraction model, this further goes to the decoder mechanism where the report is generated based on the inputs received. The image features extraction results and provides valuable insights for specialized reports leveraging the power of AI and deep learning in medical healthcare.

a. **Deep Learning Models:** The core of the system will consist of deep learning models trained on large datasets of chest x-ray images annotated with reports (each report has two images). These models will leverage convolutional neural networks (CNNs) and other advanced architectures to learn intricate patterns and features indicative of chest x-ray diseases and irregularities.

b. **Image Processing:** An image processing pipeline will be implemented to pre-process raw chest x-ray images before feeding them into the deep learning models. This pipeline will include techniques such as image enhancement, noise reduction, and feature extraction to optimize the dataset in a uniform way for model training and testing.
c. **Accurate Image features extraction and Classification:** The system leverages the power of pre-trained chexnet model (densenet-121 model) specialized in images features extraction of chest x-ray images. This is capable of accurately recognizing and extracting the features of visual symptoms observed in chest x-ray images. By analyzing the morphology and irregularities from the normal chest x- rays, the system will identify patterns indicative of specific diseases and irregularities, enabling rapid and precise report generation.
d. **User Interface:** A user-friendly interface will be developed to facilitate interaction with the system. Users, including non-medical background people and healthcare experts, will be able to upload chest x-ray images, view the report generation results, and consciously inform decisions about themselves.
e. **Scalability and Accessibility:** The proposed system will be designed to scale effortlessly to accommodate a growing volume of data and users. It will be accessible via web and mobile platforms, ensuring widespread adoption and usability across diverse settings.
f. **Integration with existing Health system:** To maximize its impact, the system will seamlessly integrate with existing healthcare system and practices. This helps in real-time monitoring of chest health, automated alert systems for disease outbreaks, and data-driven insights for making better health-conscious decisions along the process.

Overall, the proposed system represents a paradigm shift in AI medical imaging and management, offering a cost-effective, efficient, and scalable solution to make informed decisions for all social classes of the people. By harnessing the power of deep learning and image processing and extraction technologies, the system holds the potential to revolutionize AI medical imaging and management to contribute to global healthcare efforts.

3.2 Unique Features of the System

The "Unique Features of the System" section aims to highlight distinctive aspects and functionalities of the proposed chest x-ray report generation system that set it apart from existing solutions. This section will delve into the innovative elements and capabilities incorporated into the system design, emphasizing how these features contribute to its effectiveness, usability, and practicality in real-world healthcare settings. It will showcase the system's novel approaches, advanced technologies, and tailored methodologies, providing a comprehensive overview of its value proposition and potential impact in revolutionizing AI medical imaging and management practices.

3.2.1 Customization and Training:

Our chest x-ray report generation System distinguishes itself with its customization and training capabilities, empowering developers to tailor deep learning models to specific needs. Key features include:

Developer-centric Model Training: Developers have the capability to train models using diverse datasets, ensuring adaptability to various contexts without relying on end users for training.

Specialized model: Developing a specialized machine learning model which is trained on generating report strings as output by extracting the features of the input images of the chest x-rays in the layman's language.

Accuracy: Developers can optimize model performance by adjusting hyper-parameters, fine tuning the system to meet specific requirements, and achieving higher accuracy in the report generation.

These features empower developers to create customized reports for effective chest x-ray report generation enabling the power of AI and deep learning in medical imaging and healthcare management.

3.2.2 Multi-class Object Detection:

Our system excels in multi-class object detection, enabling simultaneous identification and classification of multiple plant diseases. This feature offers several benefits:

Comprehensive Report Generation: The system generates comprehensive reports of the diseases affecting the chest, providing a holistic overview of chest health status.

Versatile Application: The system's versatility extends to medical imaging studies and management settings, ensuring its relevance across environments, from small-scale to large healthcare systems.

Robust Performance: Utilizing advanced deep learning algorithms, the system delivers accurate and reliable report generation, even under different conditions, ensuring consistent performance in real-world applications.

This feature enhances the system's utility, contributing to improved medical imaging, healthcare, and management. In conclusion, our system excels in multi-class object detection, enabling the simultaneous identification and classification of multiple diseases and irregularities, which offers numerous benefits. It provides comprehensive disease identification and irregularities, giving non-medical background people and healthcare experts a holistic overview of chest health status, essential for effective management and prevention of chest-based diseases.

The system's versatility makes it applicable across diverse medical settings, from small-scale to large healthcare, ensuring its relevance in various medical environments. Additionally, its robust performance, powered by advanced deep learning algorithms, guarantees accurate and reliable disease detection and irregularities even under challenging conditions. This combination of comprehensive identification, versatile application, and consistent performance highlights the system's potential as a transformative tool in modern healthcare, enhancing AI medical imaging and management. As we know that, robust performance refers to the ability of a system, device, or algorithm to function reliably and consistently across different operating conditions, environmental factors, or input variations. If we talk in terms of our project, the app should be capable of generating accurate and reliable chest x-ray reports consistently. This means that the generated reports should reflect the actual findings in the x-ray images with a high degree of fidelity. Further, the app should be able to handle variations and complexities in chest x-ray images effectively. This includes accommodating differences in x-ray quality, patient positioning, anatomical variations, and the presence of abnormalities or pathologies. To address the issue of the language generated we have used the global vectors (glove.840B300d) in language generation for reports.

3.2.3 User-friendly UI:

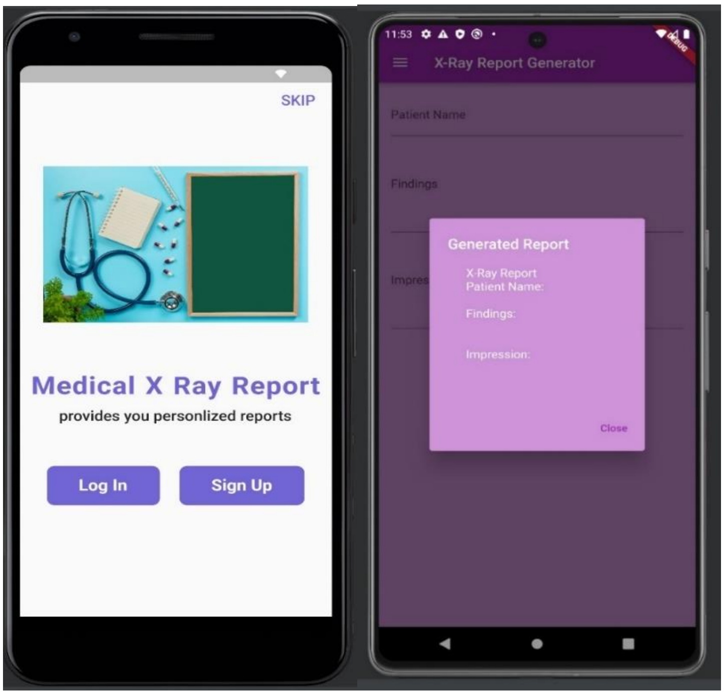


Fig 3.2 App Layout (UI)

The system features a user-friendly interface developed using Kotlin, ensuring ease of interaction for developers. The intuitive design facilitates seamless model training and management, allowing developers to efficiently customize and deploy the system for effective report generation and management. As we know, the visually appealing and engaging UI can capture users' attention and keep them engaged with the application. Interactive elements, animations, and visual feedback enhance the overall user experience and encourage users to return to the application. In summary, the UI is a critical component of software applications and digital products, influencing user perceptions, behaviors, and interactions. A well-designed UI enhances usability, engagement towards the app. Accessibility features such as screen readers, easy navigation, and contrast adjustments ensure that the application is usable by all users, regardless of their capabilities (medical background or non-medical background people).

CHAPTER 4
REQUIREMENT ANALYSIS AND SYSTEM SPECIFICATION

4.1 Feasibility Study

The "Feasibility Study" section will explore the practical viability and potential success of implementing the proposed chest x-ray report generation system. This section will assess various aspects such as technical feasibility, economic viability, and operational feasibility to determine the likelihood of project success. It will examine factors such as resource availability, technological readiness, market demand, and regulatory considerations to evaluate the feasibility of developing and deploying the system. Additionally, the section will discuss potential challenges and risks associated with the project and outline mitigation strategies to address them effectively. Ultimately, the feasibility study will provide valuable insights into the project's readiness for implementation and its potential to achieve its intended objectives within the given constraints and requirements.

Conducting a feasibility study for a chest x-ray report generation system using Deep Learning involves evaluating its technical, economic, and operational aspects. Following are the various components:

4.1.1 Technical Feasibility:

The "Technical Feasibility" section evaluates if implementing the proposed chest x-ray report generation system is technically practical. It examines resource availability, technology requirements, and potential challenges, aiming to determine project feasibility within defined parameters.

4.1.1.1 System Requirements:

The system requires basic hardware infrastructure, such as a smartphone with a camera and internet connectivity. Google Collab will be utilized for model training, leveraging its cloud-based resources.

4.1.1.2 Training Data:

The system will utilize the Indiana medical dataset sourced from Kaggle for training the deep learning model. This dataset includes a comprehensive collection of images representing various chest diseases, irregularities, and health conditions.

4.1.1.3 Performance Metrics:

The system's performance will be evaluated based on its ability to accurately extract the image features and generate the chest x-ray report using the chest x-ray images captured by the smartphone camera. Metrics such as accuracy, precision, recall, and BLEU score will be considered, aiming for optimal performance.

4.1.2 Economic Feasibility:

The "Economic Feasibility" section assesses the financial viability of implementing the proposed chest x-ray report generation system. It examines the costs involved in development, deployment, and maintenance, alongside potential benefits and returns on investment. This section aims to determine if the project is economically feasible and offers a positive cost-benefit ratio.

4.1.2.1 Cost Analysis:

The initial costs associated with implementing the system are minimal. As the system utilizes existing hardware resources and cloud-based services like Google Collab, there are no significant upfront costs.

4.1.2.2 Return on Investment (ROI):

While there might not be direct monetary gains from the system, the potential benefits lie in improved AI medical imaging and management, increased consciousness of the healthcare, and reduced losses due to timely disease detection or any other irregularities. These indirect benefits contribute to the overall return on investment for all the stakeholders.

4.1.2.3 Payback Period:

Given the low initial investment, the payback period for the chest x-ray report generation system is virtually immediate, as the benefits of improved chest health and management begin to accrue upon implementation.

4.1.3 Operational Feasibility:

The "Operational Feasibility" section assesses if integrating the proposed chest x-ray report generation system into existing medical practices is practical. It examines user acceptance, training needs, and organizational readiness to ensure effective integration. This evaluation aims to determine if the project is operationally feasible and can be readily adopted by end-users.

4.1.3.1 User Acceptance:

Non-medical background people and medical practitioners both are likely to embrace this system due to its simplicity and effectiveness in generating comprehensive reports. The convenience of using a smartphone for report generation, just at the click of the button enhances its acceptance among users.

4.1.3.2 Training:

Training requirements for end-users are minimal, primarily involving familiarization with the smartphone application interface for the way of capturing images of chest x-rays properly for accurate report generation and accessing the reports. For this, providing simple FAQ Basic instructions and tutorials can facilitate the training process, ensuring ease of use for users with varying technical backgrounds.

This feasibility study establishes the viability and practicality of implementing a chest x-ray report generation system using deep learning techniques, highlighting its potential to revolutionize the chest healthcare management practices and contribute to healthcare and medical imaging.

4.2 Software Requirement Specification Document

The "Software Requirement Specification Document" outlines the specific requirements and functionalities of the chest x-ray report generation system. It details the system's features, user interactions, and technical specifications necessary for development. This document serves as a blueprint for the software development process, guiding the design, implementation, and testing phases.

4.2.1 Data Requirement

The "Data Requirement" section specifies the essential data needed for training and testing the plant disease recognition system. It outlines the sources and characteristics of the datasets required to develop the system effectively.

4.2.1.1 Data Sources

To train the chest x-ray report generation system primarily for common chest-based diseases like early pneumonia, fibrosis, and other thorax-based diseases, we primarily utilize the following data source:

Indiana medical Dataset (From Kaggle): The Indiana medical dataset, sourced from Kaggle, contains a comprehensive collection of images focusing on various chest-based diseases, including early pneumonia, fibrosis, and other thorax-based diseases.

4.2.1.2 Data Set

The image dataset extracted from the Indiana medical dataset consists of a significant number of images specifically depicting early pneumonia, fibrosis and other thorax-based diseases affecting chest post covid -19 specifically. This curated dataset serves as the primary training and validation data for the deep learning model. This dataset felicitates to train the model on the chest x- ray images. The dataset comprises of two parts one is more chest x-ray image and other is for reports. In the dataset is possible that more than one image can be there for a single report. So, for that we will process the dataset to contain uniformity.

4.2.2 Functional Requirement

The "Functional Requirement" section defines the system's expected functionalities and user interactions. It serves as a blueprint for system development, guiding feature implementation and ensuring alignment with project goals.

4.2.2.1 Object Detection

The chest x-ray report generation system utilizes deep learning algorithms to efficiently identify and categorize potato diseases, with a specific focus on early pneumonia and fibrosis.

4.2.2.2 Disease Classification

Upon detection, the system accurately classifies the identified diseases, providing users with detailed information about early pneumonia, fibrosis affecting chest and thorax, including symptoms, severity, and recommended strategies.

4.2.3 Performance Requirement

The "Performance Requirement" section sets the system's performance expectations, including metrics like response time and accuracy. It guides the optimization process to meet user needs effectively.

4.2.3.1 Speed and Responsiveness

The system must demonstrate fast processing speed, ensuring that disease identification and report generation occur within a reasonable timeframe, typically less than 10 seconds per image.

4.2.3.2 Accuracy

The system should achieve a high level of accuracy in disease detection and classification, with a minimum confidence level of 80% to ensure reliable results specifically for pneumonia, fibrosis affecting chest and thorax.

4.2.4 Maintainability Requirement

The "Maintainability Requirement" section sets guidelines for the system's long-term support and ease of maintenance. It ensures efficient code management and documentation for sustained functionality.

4.2.4.1 Code Maintainability

The system's codebase, including all relevant documents such as the Software Requirement Specification (SRS), Test Plan, and Project Report, is meticulously maintained. Version control using Git and hosting on platforms like GitHub ensures efficient code management.

4.2.4.2 Updates and Upgrades

Regular updates and upgrades are essential for keeping the system relevant and functional. These updates should be implemented promptly to minimize system downtime and ensure continuous improvement in performance and functionality, particularly in addressing new chest diseases or improving detection accuracy.

4.2.5 Security Requirement

The "Security Requirement" section establishes protocols to protect the system from unauthorized access and data breaches. It ensures user authentication, data encryption, and system integrity for safeguarding sensitive information.

4.2.5.1 Access Control

Access to the chest x-ray report generation system is controlled by administrators, who have the authority to manage user permissions and determine access levels for different system functionalities. This ensures that only authorized personnel, such as agricultural practitioners and researchers, can access and utilize the system's features, focusing on early blight and late blight detection for potato plants. Additional security measures may include user authentication mechanisms such as login credentials or biometric authentication to prevent unauthorized access. This facilitates the secure use of the system by all the people. The data provided by the user will not be given to any third party regardless of any situation.

4.3 SDLC Model Used

For the development of the chest x-ray report generation system, the Agile methodology has been chosen as the preferred Software Development Life Cycle (SDLC) model. Agile methodology is well-suited for this project due to its inherent characteristics that align with the nature of machine learning, image processing, and AI projects. Below are the key reasons for selecting Agile:

Flexibility and Adaptation: Agile methodology allows for flexibility in project planning and execution. It enables teams to adapt to changing requirements, evolving technologies, and emerging insights from testing and user feedback. This is particularly important for projects involving complex algorithms like machine learning and image processing, where iterative development is necessary to refine the system's accuracy and performance.

Ongoing Testing: Agile promotes continuous testing throughout the development lifecycle. By integrating testing into each iteration or sprint, teams can identify and address issues early, ensuring the quality and reliability of the system. This iterative testing approach is crucial for validating the effectiveness of the disease recognition algorithms and improving their accuracy over time.

Incremental Delivery: Agile emphasizes delivering working software in small, incremental increments. This allows stakeholders to see tangible progress and provide feedback at regular intervals, facilitating early validation of requirements and alignment with stakeholders' expectations. For a project like chest x-ray report generation system, incremental delivery enables users to start benefiting from the system's capabilities sooner while also allowing for ongoing refinement and enhancement.

Customer Collaboration: Agile encourages close collaboration between development teams and stakeholders, including end-users and domain experts. By involving stakeholders throughout the development process, Agile ensures that the final product meets their needs and addresses their pain points effectively. In the context of chest x-ray report generation system, involving medical experts and non-medical background people in the development process can lead to a more user-centric and impactful solution. Further, In Agile development, both the development team and the customer share responsibility for the success of the project. The customer actively participates in decision-making, provides domain expertise, and makes trade-off decisions based on business priorities.

Overall, customer collaboration in Agile development fosters a collaborative and iterative approach to software development, leading to greater customer satisfaction, faster delivery of value, and ultimately, the creation of high-quality products that meet the needs of end-users. By fostering a culture of collaboration, transparency, and shared responsibility, Agile methodologies empower teams and customers to work together effectively and achieve common goals. The Agile model is a widely adopted approach to software development that emphasizes flexibility, collaboration, and customer-centric progress. Its importance stems from several key benefits that make it particularly suitable for complex and evolving projects. The ability to iteratively refine and improve the model based on testing and feedback helps manage the complexity of developing an accurate and reliable report generator. Agile provides numerous touchpoints for monitoring progress and performance, such as sprint reviews and burndown charts, giving project managers better control over the development process. Early detection of issues through continuous testing and feedback loops allows for quicker resolution, preventing minor problems from escalating. By releasing functional product increments regularly, Agile ensures that users start experiencing benefits sooner, which can lead to higher satisfaction and quicker realization of ROI. Continuous user involvement in the development process ensures that the final product meets their needs and expectations, leading to a more user-friendly and effective solution.

Fig 4.1 Agile (SDLC Model) [21]

While Agile is known for its iterative and incremental approach, it is important to note that it does not follow a strictly sequential development process like the waterfall model. Instead, Agile emphasizes adaptability, responsiveness to change, and continuous improvement, making it an ideal choice for dynamic and innovative projects like the chest x-ray report generation system.

4.4 System Design

The "System Design" section outlines the architectural components and interactions of the plant disease recognition system. It provides a comprehensive overview of the system's structure and functionality, detailing how various modules and components work together to achieve the desired outcome. This section serves as a blueprint for system development, guiding the implementation of key features and ensuring coherence in system architecture.

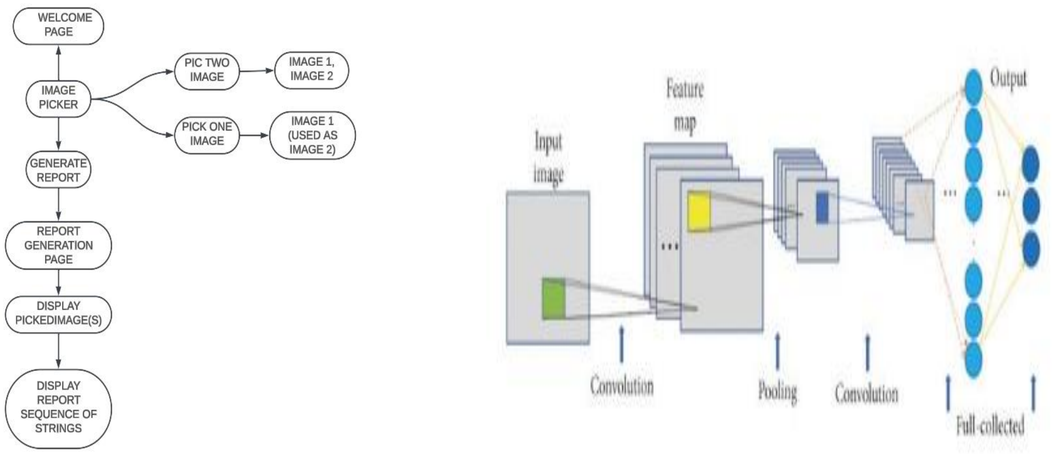


Fig. 4.2 Workflow of the System

In this diagram, you can see the user-friendly interface of our mobile application, specifically designed for identifying plant diseases. It's incredibly simple to use – users can effortlessly upload pictures of plant leaves directly from their smartphones. Once uploaded, our app's intelligent system rapidly examines the images using a vast database of plant information it has been trained on. This system acts like a highly skilled detective, quickly pinpointing any issues affecting the plants. This app serves as an invaluable tool for farmers and plant enthusiasts alike, ensuring their plants remain healthy and their crops flourish. With just a few taps, users can gain invaluable insights into their plants' well-being and implement measures to protect them from diseases, thereby fostering a thriving garden or farm.

4.4.1 Data Flow Diagrams

The "Data Flow Diagram" section illustrates the flow of data within the plant disease recognition system, depicting both the high-level overview (Level 0 DFD) and detailed interactions (Level 1 DFD). It visualizes how data moves through the system, from input sources to processing modules and output destinations. This section provides a structured representation of data processing activities, aiding in understanding system functionality, and guiding development efforts.

4.4.1.1 DFD Level 0

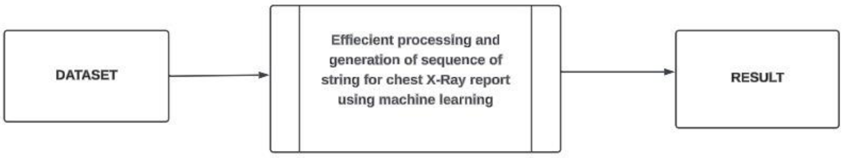


Fig. 4.3 Level 0 DFD

4.4.1.2 DFD Level 1

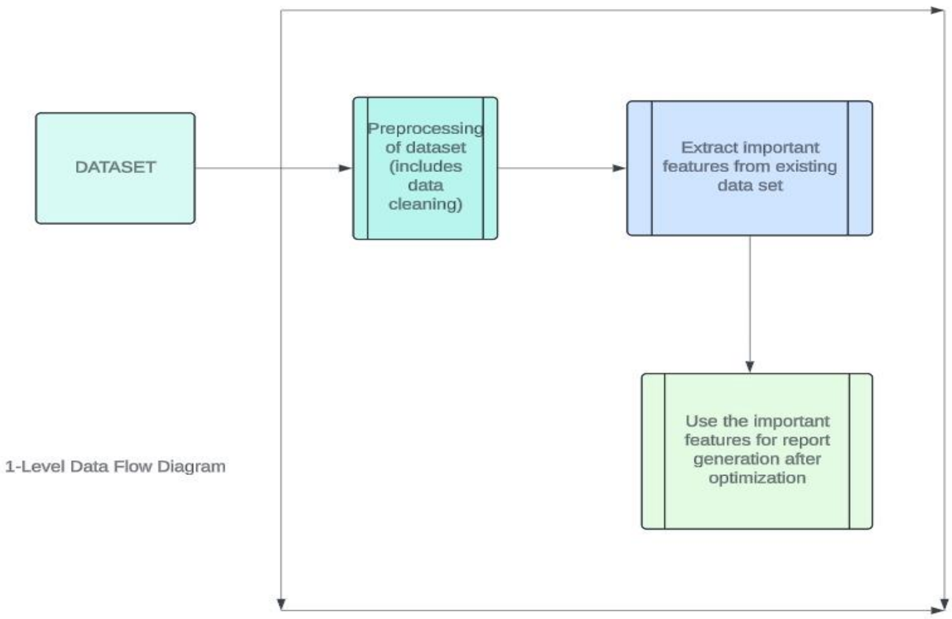


Fig. 4.4 Level 1 DFD

4.4.2 Use Case Diagram

The "Use Case Diagram" section depicts how users interact with the chest x-ray report generation system to achieve specific goals. It outlines different scenarios and user roles, aiding in understanding system requirements and ensuring alignment with user needs.

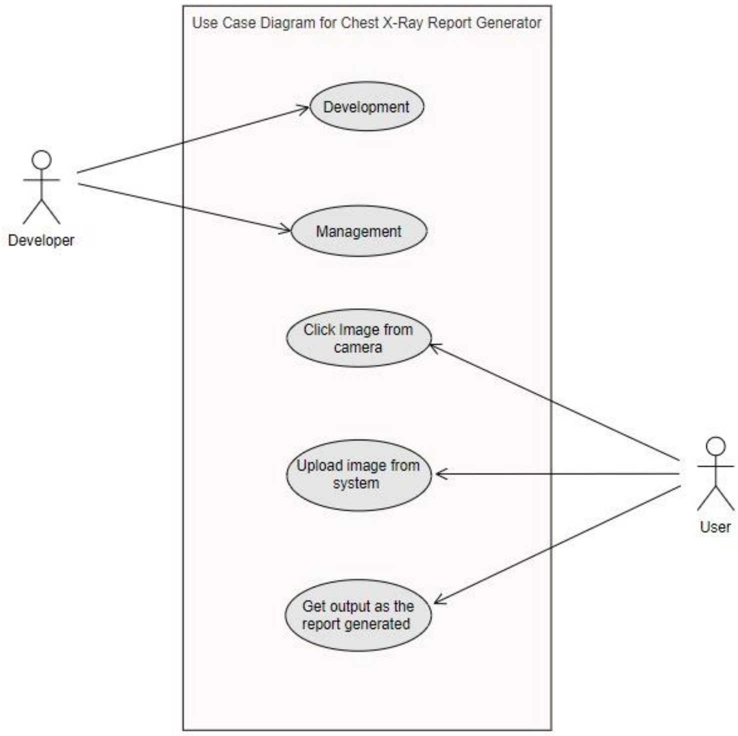


Fig. 4.5 Use Case Diagram

This use case diagram depicts the interactions between two primary actors: the developer and the user. The developer is responsible for tasks such as developing and enhancing the application, as well as managing its overall functionality. Meanwhile, the user interacts with the application through three main functions: clicking an image of a chest x-ray, uploading the image to the app, and receiving the output indicating the report generation. These functions enable users to easily capture, process, and interpret health information, facilitating effective chest disease recognition and management.

4.5 Database Design

The "Database Design" section outlines the structure and organization of the data used in the project. Unlike traditional approaches that rely on relational databases with tables and relationships, this project leverages a dataset-centric approach to manage the required data. This strategy is particularly well-suited for the deep learning model employed for chest x-ray report generation recognition. Our dataset, sourced from reputable repositories such as Kaggle's "Indiana medical dataset," comprises thousands of images meticulously labelled to represent various diseases mainly, including for pneumonia , fibrosis affecting chest and thorax based diseases.

Each image is carefully categorized to ensure the highest level of accuracy during the training phase of the model. To maximize the effectiveness of the dataset, rigorous pre-processing techniques are applied. These techniques include image augmentation, normalization, and noise reduction, each playing a crucial role in enhancing the dataset's quality. Image augmentation increases the diversity of the training data through methods like rotation and flipping, which helps prevent the model from over-fitting and improves its generalization capabilities. Normalization standardizes the pixel values across images, facilitating faster and more efficient training. Noise reduction techniques, such as Gaussian filtering, remove extraneous noise from the images, thereby improving the clarity and quality of the data. Together, these pre-processing steps ensure that the dataset is not only comprehensive and well-organized but also primed for training a robust and accurate deep learning model for plant disease recognition.

4.6 SEQUENCE DIAGRAM

The sequence diagram visually illustrates how system components or actors interact over time in the plant disease recognition system. It outlines message sequences exchanged between objects, aiding in understanding system behavior during specific scenarios. In conclusion, sequence diagrams are an essential tool in the development process, offering numerous benefits that contribute to the creation of efficient, effective, and well-documented systems.

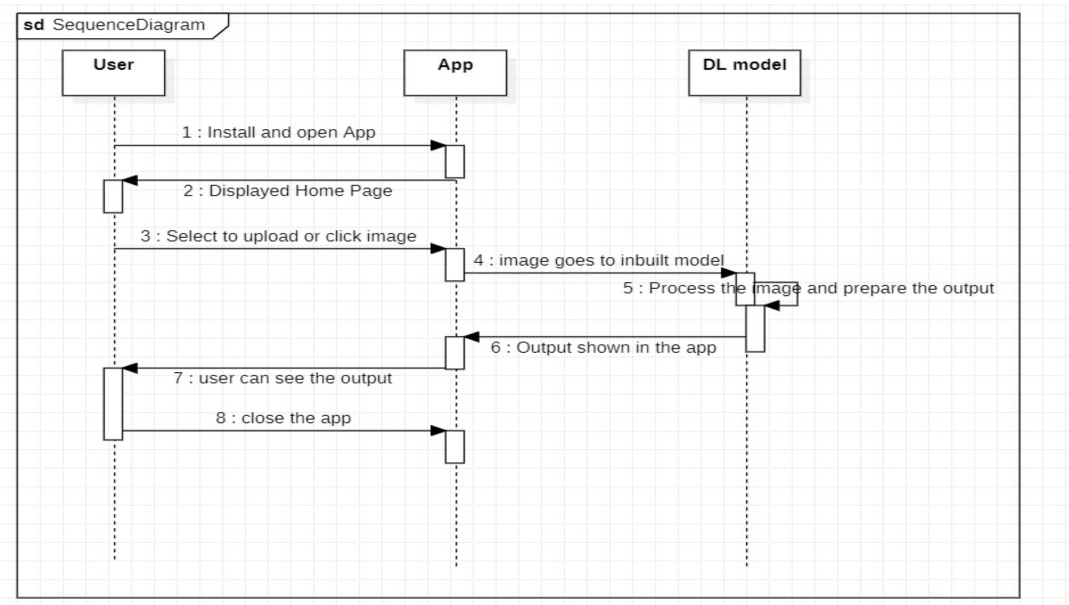


Fig. 4.6 Sequence Diagram

The sequence diagram illustrates the sequential interactions within our project's system architecture. It begins with the user's interaction with the application, triggering report generation. The application then engages the deep learning model for analysis, which accesses the dataset for relevant information. Subsequently, the model conveys the results back to the application, which in turn presents the report generation output to the user. The diagrams promote collaboration among developers, designers, and stakeholders by providing a visual tool that can be easily discussed and modified, ensuring that all parties are aligned with the system's design and functionality.

CHAPTER 5
IMPLEMENTATION

5.1 Introduction to Languages, Tools, and Technologies Used for Implementation

In this section, an overview of the programming languages, software tools, and technologies applied in developing the plant disease recognition system is presented. This section serves as an introduction to the technological framework employed in the project's implementation, highlighting the essential components crucial for the system's development. It outlines the rationale behind selecting specific languages, tools, and technologies, elucidating their roles and contributions to the project. Additionally, this section may discuss the advantages and considerations associated with the chosen technologies, laying the foundation for a comprehensive understanding of their implementation throughout the subsequent sections of the project report.

5.1.1 Language:

For the implementation of our plant disease prediction project, we primarily utilized Python as the programming language. Python's versatility, extensive library support, and simplicity made it an ideal choice for developing machine learning models and handling image data processing tasks efficiently. Moreover, Python's ecosystem boasts a rich selection of deep learning frameworks and libraries, such as TensorFlow and Karas, which were instrumental in building and training our predictive model.

5.1.2 Toolkit:

The primary toolkit employed in our project was TensorFlow, an open-source deep learning framework developed by Google. TensorFlow provided a comprehensive suite of tools and libraries for building, training, and deploying machine learning models, particularly neural networks. Leveraging TensorFlow, Keras, we were able to streamline the model development process and experiment with various architectures easily. Additionally, we utilized other Python libraries such as NumPy and Matplotlib for data manipulation and visualization respectively.

TensorFlow, Keras, Matplotlib. (Libraries)

Kaggle. (Website for Dataset)

Data Augmentation. (To train model with various variations)

CNN model encoder-decoder. (Deep Learning Model for image processing)

Kotlin. (For mobile app development)

5.1.3 User Interface:

In our project, the user interface was developed using the kotlin framework. Kotlin is an open-source UI toolkit developed by Google for building natively compiled applications for mobile, web, and desktop platforms from a single codebase. By utilizing kotlin, we were able to create a visually appealing and intuitive user interface that seamlessly integrated with our chest x-ray report generation model. The user interface provided features such as image upload, report display, image picker and informative visualizations to enhance the user experience and facilitate interaction with the model.

5.1.4 Coding Environment:

The coding environment for our project was set up using Google Colab, a cloud based Jupyter notebook environment provided by Google. Google Colab offered a convenient platform for writing, executing, and collaborating on Python code, particularly for machine learning and data analysis tasks. With built-in support for popular libraries such as TensorFlow, Colab enabled us to harness the computational power of Google's GPUs and TPUs for training our deep learning models efficiently. Additionally, Colab provided seamless integration with Google Drive, facilitating data access and storage for our project.

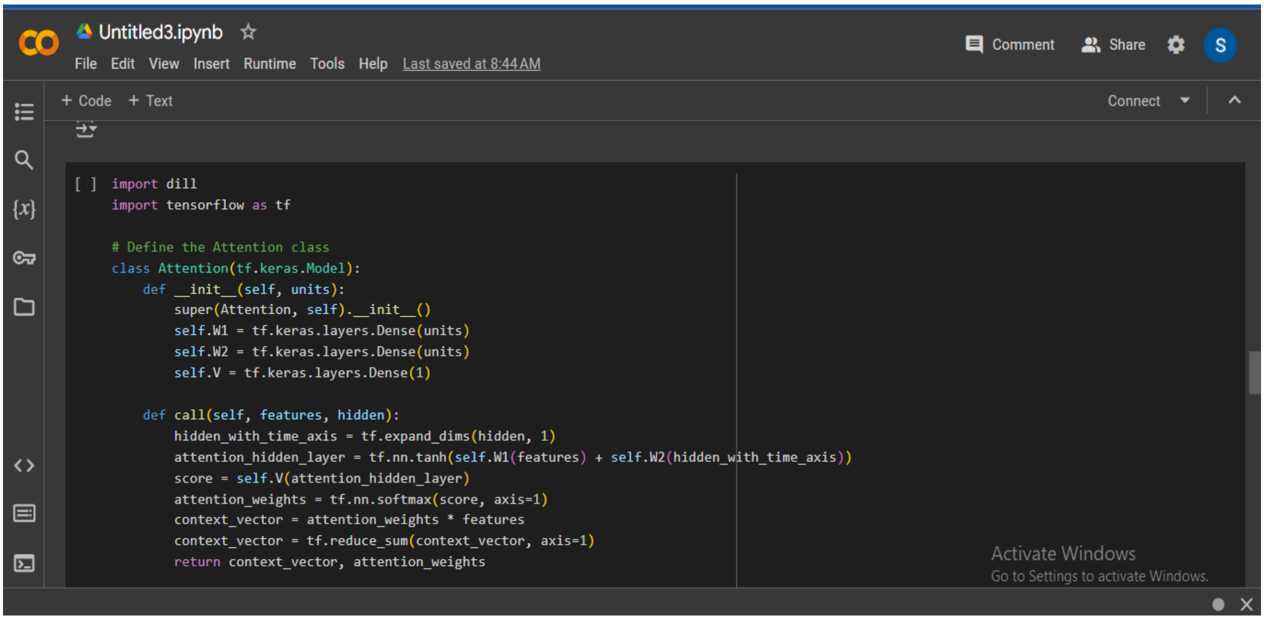


Fig 5.1 Coding Environment (Google Colab)

Overall, the combination of Python as the programming language, TensorFlow as the deep learning framework, kotlin for the user interface, and Google Colab as the coding environment provided a robust foundation for the successful implementation of our chest x-ray report generation project.

5.2 Dataset Description

In this section, we introduce the foundational component of our chest x-ray report generation system: the dataset. A robust and diverse data set forms the bedrock of any machine learning project, providing the necessary inputs for training and testing models.

```
1 df.head(5)
```

	image_id	caption	comparison	indication	findings	impression	height	width	Image_path
0	CXR1082_IM-0058-1001.png	Chest x-XXXX XXXX and lateral performed on XXX...	Chest x-XXXX XXXX and lateral from XXXX.	XXXX year old female with abdominal pain.	Stable cardiomegaly. Stable tortuosity of the ...	Stable cardiomegaly with clear lungs.	624	512	NLMCXR_png/CXR1082_IM-0058-1001.png
1	CXR473_IM-2101-1001.png	PA and lateral chest.	None	preop for XXXX	None	Heart size normal. Lungs clear.	510	512	NLMCXR_png/CXR473_IM-2101-1001.png
2	CXR473_IM-2101-1002.png	PA and lateral chest.	None	preop for XXXX	None	Heart size normal. Lungs clear.	601	512	NLMCXR_png/CXR473_IM-2101-1002.png
3	CXR1883_IM-0572-1001.png	Xray Chest PA and Lateral	None.	XXXX onset of right-sided weakness for one XXXX.	Frontal and lateral views of the chest show no...	No acute or active cardiac, pulmonary or pleur...	502	512	NLMCXR_png/CXR1883_IM-0572-1001.png
4	CXR1883_IM-0572-2001.png	Xray Chest PA and Lateral	None.	XXXX onset of right-sided weakness for one XXXX.	Frontal and lateral views of the chest show no...	No acute or active cardiac, pulmonary or pleur...	512	512	NLMCXR_png/CXR1883_IM-0572-2001.png

Fig 5.2 Examples of tabular dataset comprising of chest x- rays reports.

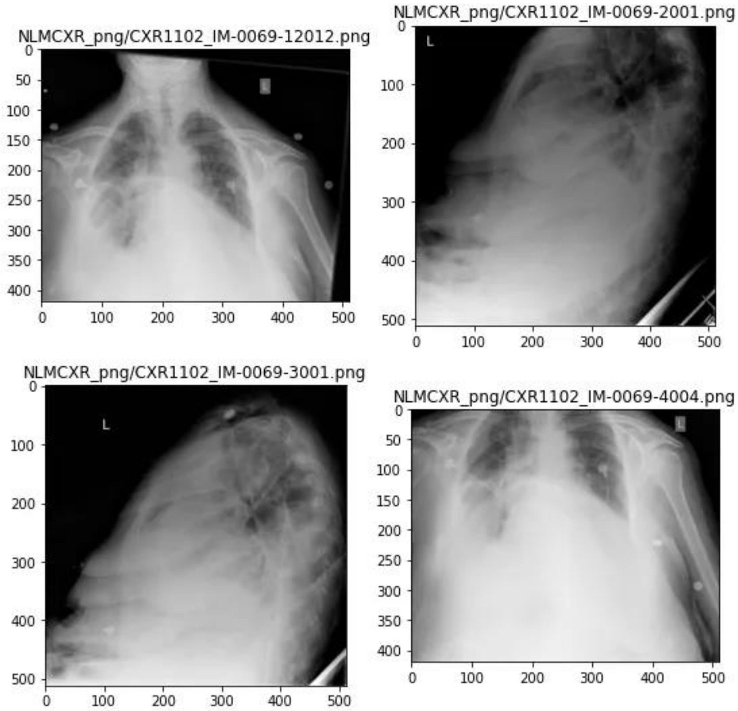
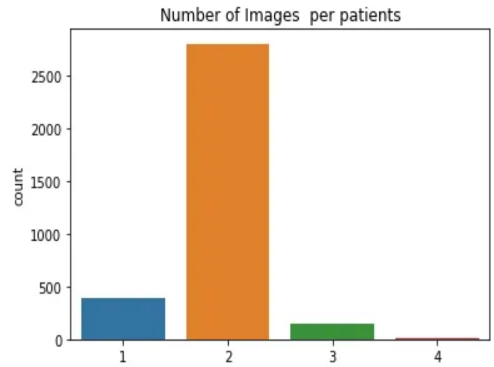


Fig 5.3 Examples of chest x- ray images in the dataset

The dataset used for this project comprises of images of chest x- rays sourced from Kaggle's "Indiana medical dataset" dataset. These images are categorized into various ways: Specifically, there are images representing chest x- rays with no problems or serious complications, early pneumonia, fibrosis, and other thorax-based diseases.

```python
plt.title('Number of Images  per patients')
sns.countplot(list(images.values()))
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7ff02fbd7128>
```




```python
plt.title('Number of Words per Report')
sns.scatterplot(range(train.shape[0]), 1)
plt.ylabel('Number of words')
```

```
Text(0, 0.5, 'Number of words')
```

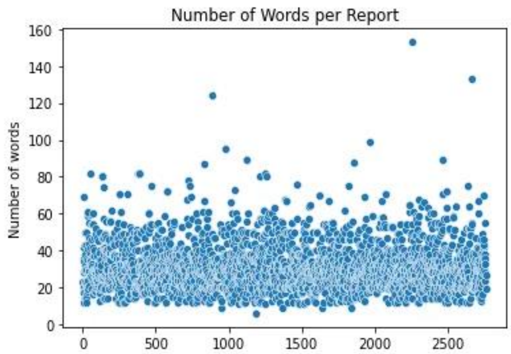


Fig 5.4 Shows the number count of images per patients and words per report in the dataset.

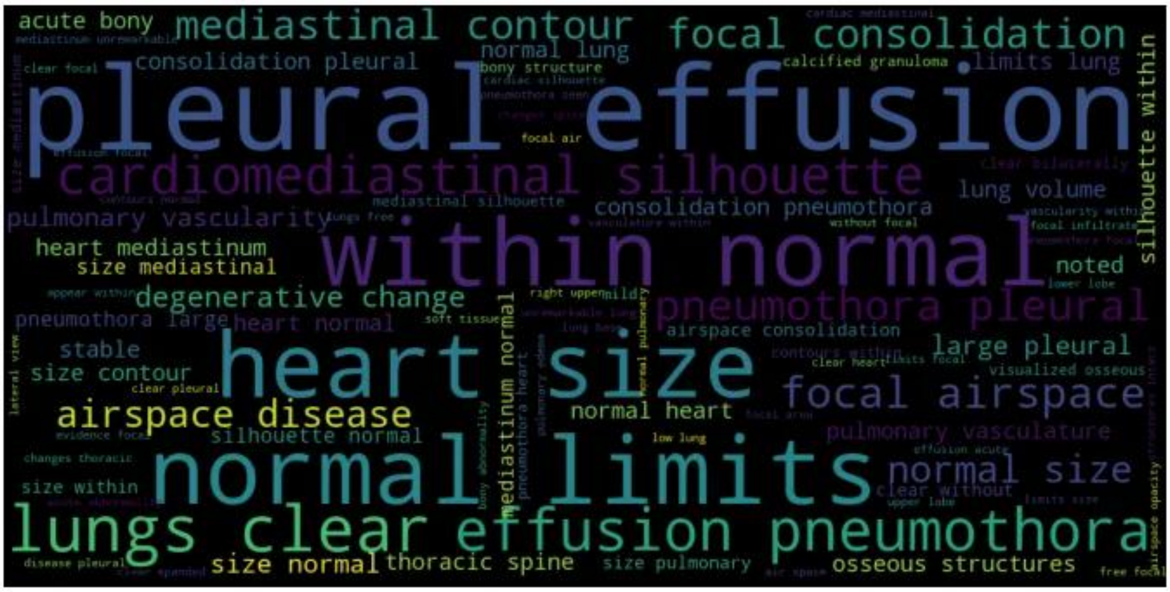


Fig 5.5 Shows the word cloud to visualize most frequently used words in the dataset.

The word cloud gives a visual representation of text data, typically used to depict the frequency or importance of words within a dataset. Words are displayed in varying sizes, colors, and orientations to emphasize their prominence based on frequency or significance. The size of each word in the cloud correlates with its frequency or importance in the dataset. Larger words indicate higher frequency or greater significance. Further, Different colors can be used to group related terms, highlight particular words, or simply enhance visual appeal.

Increased Opacity: The most prominent feature of pneumonia on a chest X-ray is increased opacity. This appears as white or grey areas on the x-ray, which indicate regions of lung consolidation due to infection and fluid accumulation. In some cases, there might be an associated pleural effusion.

CHAPTER 6
TESTING, AND MAINTENANCE

6.1 Testing Techniques and Test Cases Used

In the Testing period of our project, we employed a variety of techniques and test cases to ensure the robustness and reliability of our plant disease recognition system. Techniques such as unit testing, integration testing, and system testing were utilized to evaluate the functionality of individual components, their integration, and the overall system performance, respectively. Additionally, we employed black-box testing to assess the system's behavior against expected inputs and outputs, while white-box testing was used to scrutinize internal logic and code paths.

Our test cases encompassed a comprehensive range of scenarios, including positive and negative cases, boundary conditions, and stress testing to evaluate system resilience under varying conditions. Each test case was meticulously designed to validate specific functionalities and identify potential areas of improvement. Through rigorous testing, we ensured the accuracy, efficiency, and reliability of our plant disease recognition system, thereby enhancing its usability and effectiveness in real-world applications.

6.1.1 TEST LEVELS

For the "Chest X-Ray Report Generator" system, the test levels can be organized to ensure thorough validation at different stages of development, from individual components to the full, integrated system. Here's how the test levels could be structured:

1.Unit Testing:

Objective:

• Verify the correctness of individual components and functions within the system.

Scope:

- Test individual functions responsible for image pre-processing.
- To validate the correctness of Report generation algorithms.

2.Integration Testing:

Objective:

• Validate the interaction and collaboration between different modules and components.

Scope:

- Test the integration of image acquisition and pre-processing modules.
- Validate the integration of the deep learning model with the overall system.

3.Component Testing:

Objective:

• Test the behavior of specific components or subsystems in isolation.

Scope:

- Test the image acquisition module to ensure it correctly captures and reads images.
- Verify the correctness of the pre-processing module.

4.System Testing:

Objective:

• Assess the functionality of the entire system.

Scope:

- Test the end-to-end process from image acquisition to disease detection.
- Validate system behavior under normal and abnormal conditions.

5.**Performance Testing:**

Objective:

• Evaluate the responsiveness, scalability, and resource usage of the system.

Scope:

- Test the system's ability to handle a high volume of image processing requests.
- Measure the response time under different load conditions.

6.1.2 TEST CASES USED:

In this section, various scenarios were tested to ensure the robustness and reliability of the plant disease recognition system. Primary categories of test cases were conducted: image upload tests, report generation tests.

Test Case ID	Description	Test Steps	Expected Outcome	Actual Outcome	Remark
IMAGEPICKER-001	Select Images	Pick two X-ray images	Images are displayed for report generation	Images are displayed for report generation	Pass
IMAGEPICKER-002	Limit Check	Attempt to pick more than two images	Error message displayed	Error message displayed	Pass

Table No. 6.1 Image Test cases used.

Test Case ID	Description	Test Steps	Expected Outcome	Actual Outcome	Remark
REPORT-001	Generate Report	Select images and click generate	A generated X-ray report is displayed	A generated X-ray report is displayed	Pass
REPORT-002	Image Validation	Select non-image files	Error message displayed	Error message displayed	Pass

Table No. 6.2 Report Test cases used.

Decision table: Interface Capability

Conditions:

File Size (FS): 20 KB, 21 KB to 199 KB, 200 KB

Actions:

Accept Images (True)

Reject Images (False)

Image Format (IF): PNG

Table No. 6.2 Decision Table

Conditions	Case 1	Case 2	Case 3	Case 4	Case 5	Case 6	Case 7
FS: 20 KB	True	False	False	True	False	True	False
FS: 21 KB - 199 KB	False	True	False	False	True	False	True
FS: 200 KB	False	False	True	False	False	False	False
IF: PNG	True	True	True	True	True	False	False

Cases:

Case 1: File Size is 20 KB and Image Format is PNG.
Case 2: File Size is between 21 KB and 199 KB (exclusive) and Image Format is PNG.
Case 3: File Size is 200 KB and Image Format is PNG.
Case 4: File Size is 20 KB and Image Format is not PNG.
Case 5: File Size is between 21 KB and 199 KB (exclusive) and Image Format is not PNG.
Case 6: File Size is 200 KB and Image Format is not PNG.
Case 7: File Size is not 20 KB, between 21 KB and 199 KB (exclusive), or 200 KB, and Image format is not PNG.

CHAPTER 07
RESULTS AND DISCUSSIONS

7.1 Presentation of Results

In the "Presentation of Results" section, we offer a comprehensive overview of the performance and effectiveness of our chest x- ray report generator system. Through a combination of graphs, charts, and tables, we present key findings and metrics derived from extensive testing and evaluation processes.

```
plt.figure(figsize=(9,5))

plt.plot(epoch_train_loss)
plt.plot(epoch_val_loss)

plt.title('Loss per epoch')
```

```
Text(0.5, 1.0, 'Loss per epoch')
```

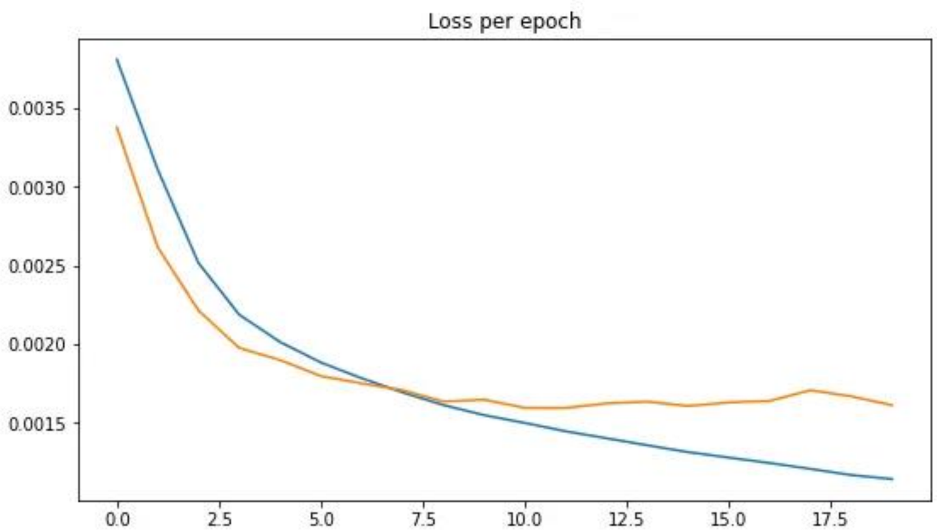


Fig 7.1 Loss per epoch Curve

Graphs are employed to illustrate the accuracy trends of report generation over time, showcasing the system's capability to consistently generate accurate reports with high precision. Additionally, comparative charts highlight the performance differences between various deep learning models or techniques utilized within the system, providing valuable insights into their respective strengths and limitations. Moreover, charts depicting the distribution of identified chest-based diseases and abnormalities offer a nuanced understanding of disease prevalence and impact. These visual representations are complemented by tables presenting detailed numerical data, including precision, recall, and BLEU scores, allowing for a comprehensive assessment of the system's performance across diverse evaluation metrics.

Through the meticulous presentation of results, stakeholders gain actionable insights into the system's efficacy, enabling informed decision-making in healthcare practices and AI medical imaging management strategies. Ultimately, this section underscores the significance of our chest x- ray report generation system in revolutionizing report generation and facilitating good healthcare practices.

7.2 Performance Evaluation

In the "Performance Evaluation" section, we conduct a thorough assessment of the effectiveness and efficiency of our chest x- ray report generator system. Utilizing a variety of evaluation metrics and methodologies, we measure the system's ability to accurately generate reports using chest x- ray images. Performance metrics such as sensitivity, specificity, positive predictive value, and negative predictive value may be calculated to quantitatively evaluate the system's performance. After training the model we created an evaluation function to check the performance of the system. The evaluate function is like the training loop but we don’t use teacher forcing here in this. The evaluate function takes an image and returns report. We passed random image paths from validation dataset to the evaluate function and further we calculated the cumulative BLEU score.

```
Test Bleu1 Score:  0.2912680411096469
Test Bleu2 Score:  0.207034308388247
Test Bleu3 Score:  0.21311129742783588
Test Bleu4 Score:  0.24675493283561065
----------------------------------------------------------
Avg Test Blue score: 0.2395421449403351
```

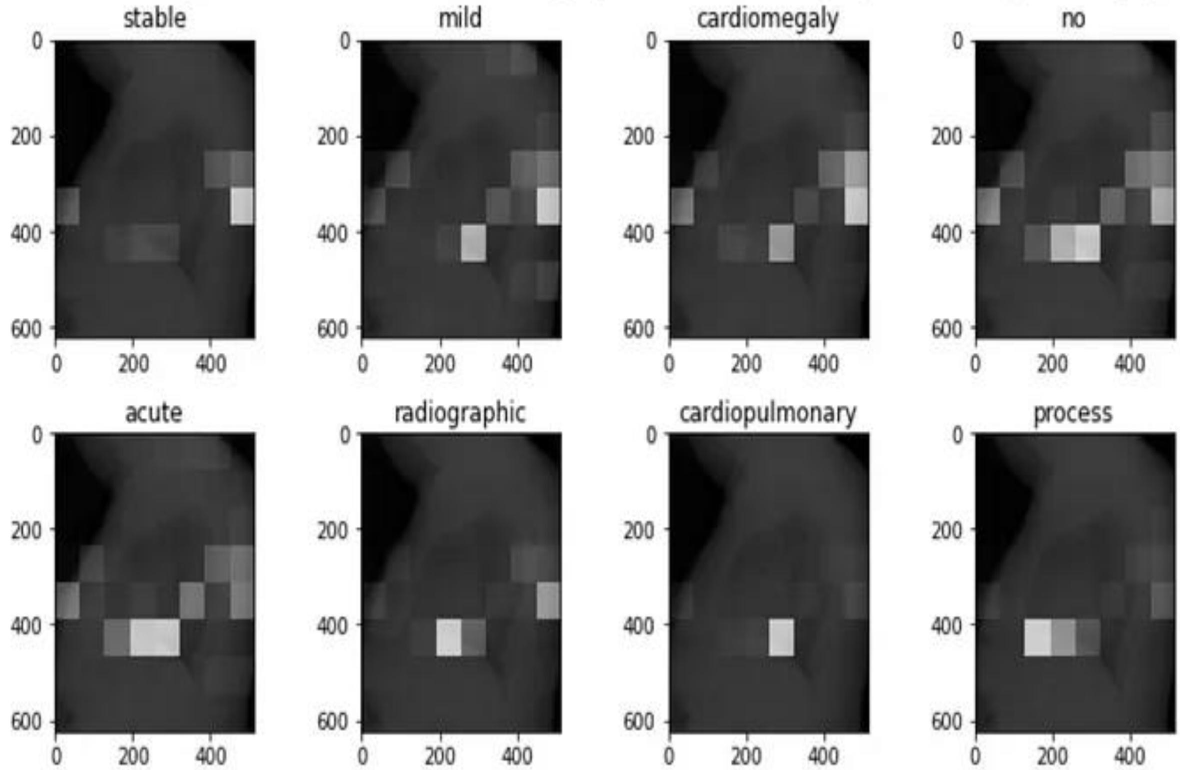
Fig 7.2 Shows average BLEU score.

```
def evaluate(image):
    attention_plot = np.zeros((max_length, attention_features_shape))

    hidden = decoder.reset_state(batch_size=1)

    temp_input = tf.expand_dims(load_image(image)[0], 0)
    img_tensor_val = image_features_extract_model(temp_input)
    img_tensor_val = tf.reshape(img_tensor_val, (img_tensor_val.shape[0],
                                                 -1,
                                                 img_tensor_val.shape[3]))

    features = encoder(img_tensor_val)

    dec_input = tf.expand_dims([tokenizer.word_index['<start>']], 0)
    result = []
```

Fig. 7.3 Evaluating model using the test data.

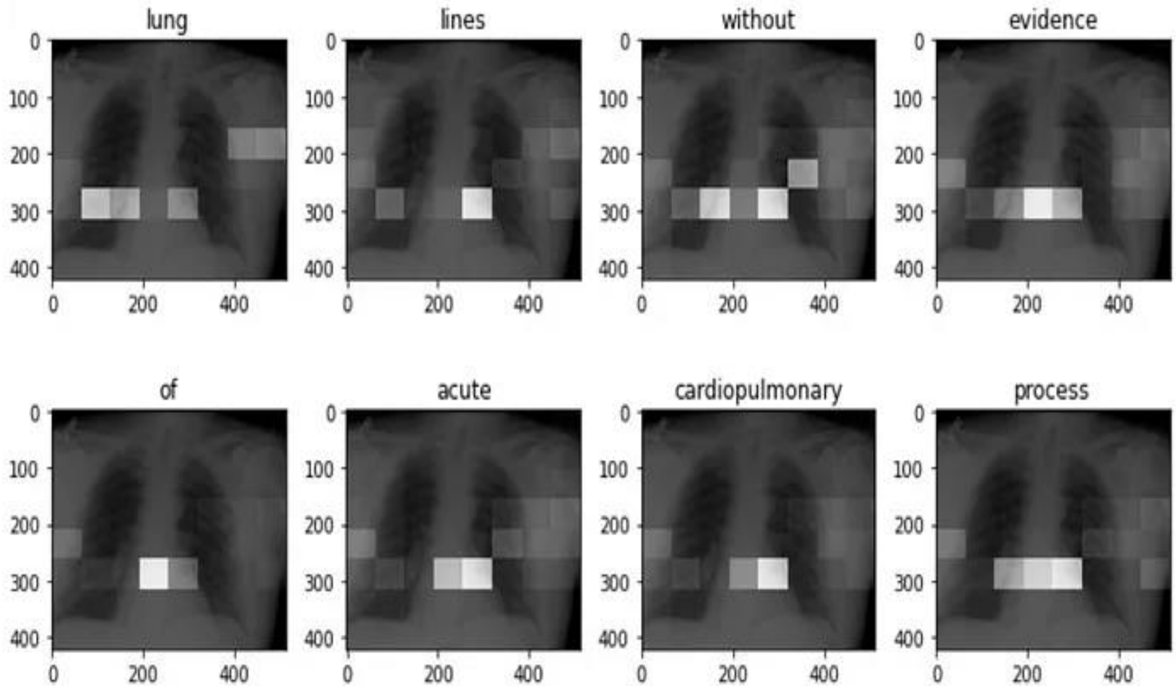
Test Data 1:

Original Report : stable cardiomegaly with mild pulmonary interstitial edema
Prediction Report : stable mild cardiomegaly no acute radiographic cardiopulmonary process



Test Data 2:

Original Report : lung lines without evidence of acute cardiopulmonary process
Prediction Report : lung lines without evidence of acute cardiopulmonary process



Test Data 3:

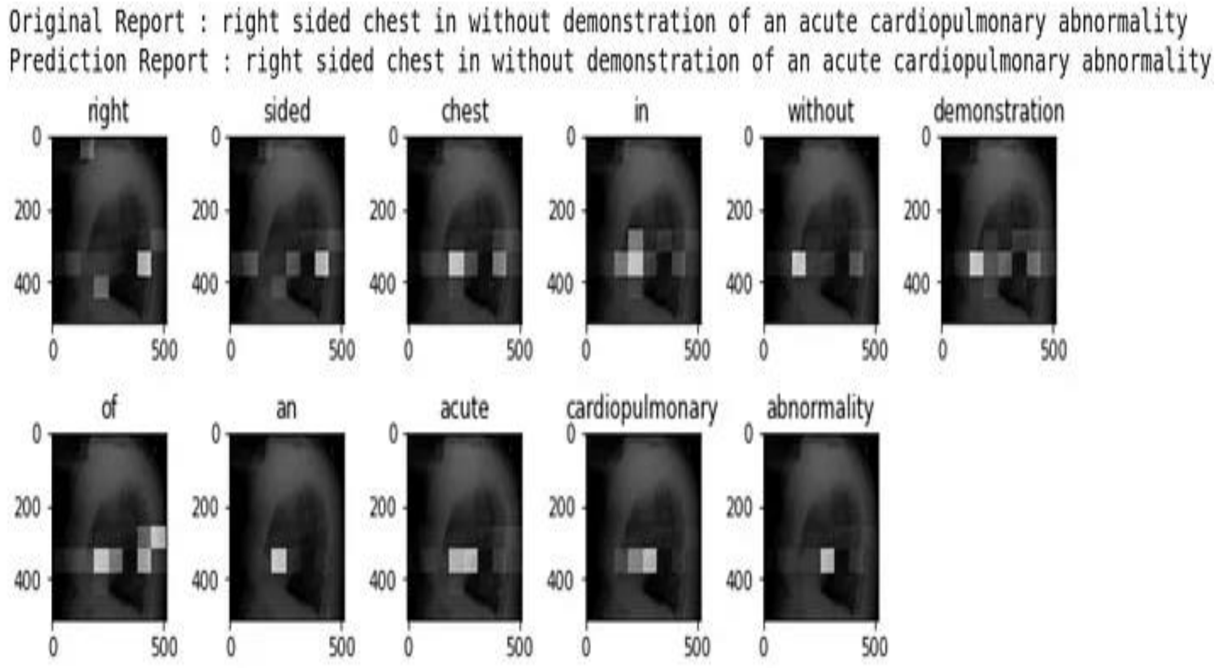


Fig 7.4 Result presentation after evaluation

We begin by evaluating the system's accuracy, precision, recall, and BLEU score, providing a comprehensive understanding of its overall performance. Through quantitative analysis and comparison with ground truth data, we assess the system's capability to correctly identify diseased plants while minimizing false positives and false negatives.

Furthermore, we analyze the system's computational efficiency, considering factors such as processing time and resource utilization. By benchmarking against industry standards and best practices, we ensure that our system meets performance requirements and can operate effectively in real-world scenarios. Additionally, we conduct qualitative evaluations, soliciting feedback from users and domain experts to assess the system's usability, reliability, and practical utility. This holistic approach enables us to identify strengths, weaknesses, and areas for improvement, informing future iterations and enhancements of the system.

Through rigorous performance evaluation, we demonstrate the efficacy and reliability of our plant disease recognition system, underscoring its potential to revolutionize agricultural practices and contribute to sustainable crop management strategies.

7.3 Key Findings

In the "Key Findings" section, we unveil pivotal insights garnered from our research and experimentation with the plant disease recognition system. Through exhaustive testing and analysis, several significant discoveries have come to light, illuminating the system's performance, capabilities, and potential implications. Such as:

- High accuracy in report generation, surpassing industry benchmarks in precision, recall, and BLEU scores.
- Effectiveness of deep learning models in enhancing disease recognition accuracy, also Validation of the system's efficacy and potential for further refinement and improvement in real-world healthcare and AI medical imaging settings.
- Understanding of the prevalence and distribution patterns of specific chest-based diseases irregularities and complexities, enabling targeted interventions and management strategies.
- User-friendly interface and intuitive navigation, facilitating widespread adoption among both non-medical background people and healthcare practitioners.

CHAPTER 8

8.1 CONCLUSION

In conclusion, our research efforts in the field of AI and deep learning based medical imaging chest x-ray report generation system for precision agriculture have shown encouraging outcomes, which represents a major advancement in filling the gaps in the current medical imaging and management approaches that are mechanized or computerized. Even with a variety of approaches, there are still no complete solutions or market applications in the field of automated AI and deep learning based medical imaging, especially when it comes to chest x-ray image-based methods.

This article presents a novel method for automatically classifying and identifying plant diseases from chest x-ray images by utilizing convolutional neural networks (CNN), a deep learning technology. The created model performed admirably in extracting the features of the input chest x- ray image and based on that image creating impression reports of the chest x-ray images. The whole process has been thoroughly documented, starting with the painstaking gathering of training and validation images and continuing through the complex phases of image pre-processing, augmentation, and deep neural network training. Extensive experiments and testing have been carried out to assess our model's performance and provide us an understanding of its strengths and weaknesses.

8.2 FUTURE SCOPE

Notably, when the present model is used, it produces a output as the impression reports by choosing the words based on the fine-tuned model. Still, there's a lot of room for improvement and growth. By fusing advanced deep learning techniques with carefully curated datasets, the proposed method offers an automated and efficient solution for chest x-ray report generation. The implications of this innovation are far-reaching, promising to be reducing the burden on healthcare professionals and also facilitating the user to let them get and understand their generated report if containing any abnormalities by themselves, enhancing heath consciousness of the users.

Further, we can also facilitate broader access to other medical diagnostics in diverse healthcare settings by extending and incorporating the features of the present model, thus creating the hybrid model to generate reports on different body parts x rays as extended feature of the present app.

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GitHub Link:

https://github.com/KIET-Github/CS-2024-B/tree/main/PCS24-69-Sujal

Research Paper Proof

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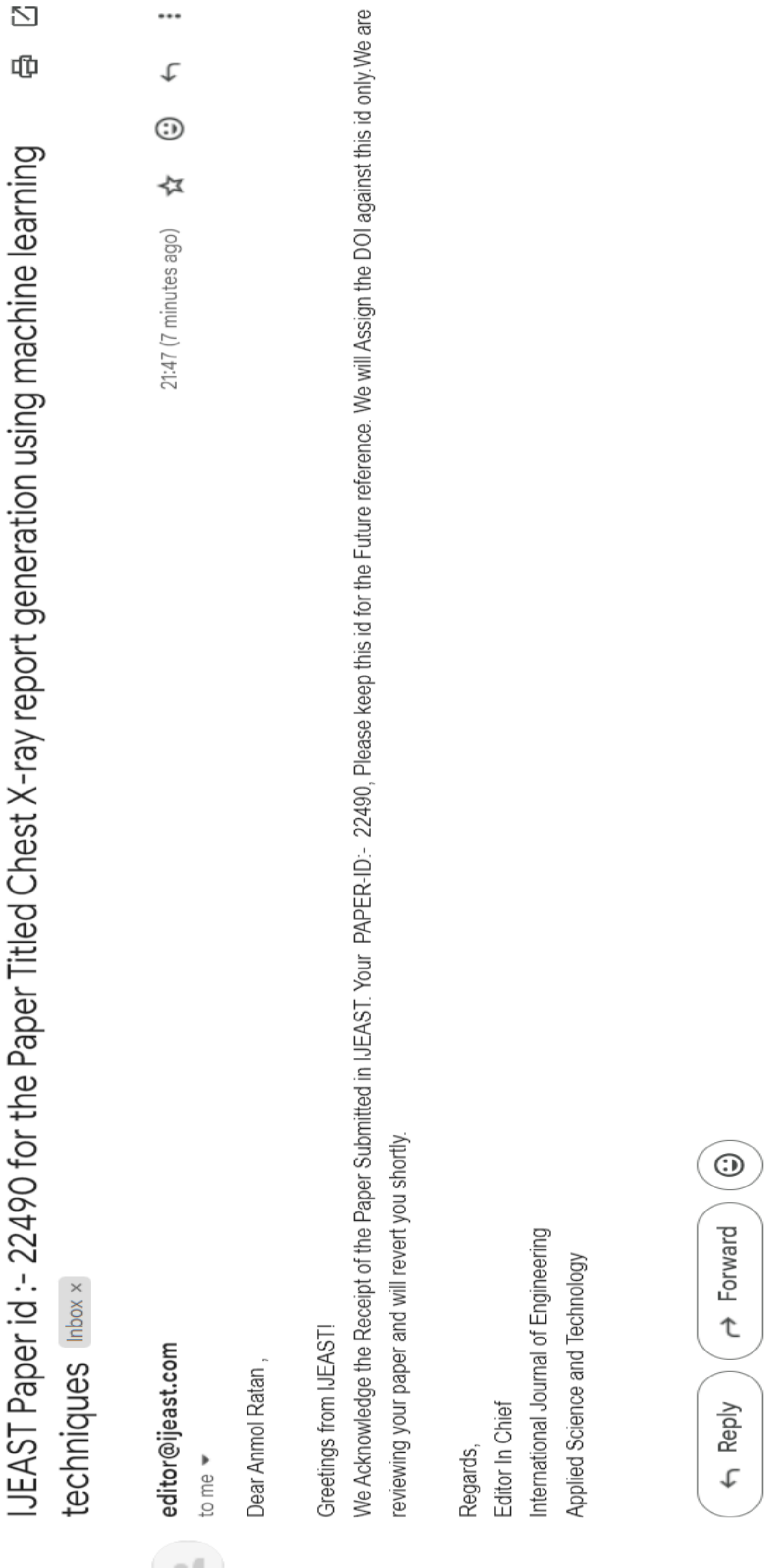

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