Towards High-Throughput Medical Image Analysis With Quantum Image Processing

A Project Report submitted in the partial fulfillment

of the Requirements for the award of the degree

BACHELOR OF TECHNOLOGY

IN

COMPUTER SCIENCE AND ENGINEERING

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CERTIFICATE

This is to certify that the project that is entitled with the name "Towards High - Thorughput Medical Image AnalaysisWith Quantum Image Processing" is a bonafide work done by the team S.Bhavani (21471A0552), K.Deepika (21471A0518), K.Tejaswini (21471A0530)in partial fulfillment of the requirements for the award of the degree of BACHELOR OF TECHNOLOGY in the Department of COMPUTER SCIENCE AND ENGINEERING during 2024-2025.

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We declare that this project work titled " TOWARDS HIGH-THROUGHPUT MEDICAL IMAGE ANALYSIS WITH QUANTUM IMAGE PROCESSING " is composed by ourselves that the work contain here is our own except where explicitly stated otherwise in the text and that this work has been submitted for any other degree or professional qualification except as specified.

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PEO3: Work with ethical and moral values in the multi-disciplinary teams and can communicate effectively among team members with continuous learning.

PEO4: Pursue higher studies and develop their career in software industry.

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3. **Design/development of solutions:** Design solutions for complex engineering problems and design system components or processes that meet the specified needs with appropriate consideration for the public health and safety, and the cultural, societal, and environmental considerations.
4. **Conduct investigations of complex problems:** Use research-based knowledge and research methods including design of experiments, analysis and interpretation of data, and synthesis of the information to provide valid conclusions.
5. **Modern tool usage:** Create, select, and apply appropriate techniques, resources, and modern engineering and IT tools including prediction and modeling to complex engineering activitieswith an understanding of the limitations.
6. **The engineer and society:** Apply reasoning informed by the contextual knowledge to assess societal, health, safety, legal and cultural issues and the consequent responsibilities relevant to the professional engineering practice.
7. **Environment and sustainability:** Understand the impact of the professional engineeringsolutions in societal and environmental contexts, and demonstrate the knowledge of, and need for sustainable development.
8. **Ethics:** Apply ethical principles and commit to professional ethics and responsibilities and norms of the engineering practice.
9. **Individual and team work:** Function effectively as an individual, and as a member or leader in diverse teams, and in multidisciplinary settings.
10. **Communication:** Communicate effectively on complex engineering activities with the engineering community and with society at large, such as, being able to

comprehend and write effective reports and design documentation, make effective presentations, and give and receive clear instructions.

11. **Project management and finance:** Demonstrate knowledge and understanding of the engineering and management principles and apply these to one's own work, as a member and leader in a team, to manage projects and in multidisciplinary environments.
12. **Life-long learning:** Recognize the need for, and have the preparation and ability to engagein independent and life-long learning in the broadest context of technological change.

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Project Course Outcomes (CO'S):

CO421.1: Analyse the System of Examinations and identify the problem.

CO421.2: Identify and classify the requirements.

CO421.3: Review the Related Literature.

CO421.4: Design and Modularize the project.

CO421.5: Construct, Integrate, Test and Implement the Project.

CO421.6: Prepare the project Documentation and present the Report using appropriate method.

Course Outcomes – Program Outcomes mapping

	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PO12	PSO1	PSO2	PSO3
C421.1		✓											✓		
C421.2	✓		✓		✓								✓		
C421.3				✓		✓	✓	✓					✓		
C421.4			✓			✓	✓	✓					✓	✓	
C421.5					✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
C421.6									✓	✓	✓		✓	✓	

Course Outcomes – Program Outcome correlation

	PO1	PO2	PO3	PO4	PO5	PO6	PO7	PO8	PO9	PO10	PO11	PO12	PSO1	PSO2	PSO3
C421.1	2	3											2		
C421.2			2		3								2		
C421.3				2		2	3	3					2		
C421.4			2			1	1	2					3	2	
C421.5					3	3	3	2	3	2	2	1	3	2	1
C421.6									3	2	1		2	3	

Note: The values in the above table represent the level of correlation between CO's and PO's:

1. Low level
2. Medium level
3. High level

Project mapping with various courses of Curriculum with Attained PO's:

Name of the Course from Which Principles Are Applied in This Project	Description of the Task	Attained PO
C2204.2, C22L3.2	Developing a deep learning-based model using CheXNet-LSTM with CLAHE + MHA to automatically generate radiology reports from frontal and lateral chest X-ray images for improved diagnosis.	PO1, PO3
CC421.1, C2204.3, C22L3.2	Critically analyzing chest X-ray report generation requirements and selecting appropriate deep learning models like CheXNet-LSTM with CLAHE + MHA for effective experimentation.	PO2, PO3
CC421.2, C2204.2, C22L3.3	Designing UML diagrams and refining feature extraction for Chest X-ray report generation.	PO3, PO5, PO9
CC421.3, C2204.3, C22L3.2	Testing, integrating, and evaluating CNN-LSTM models with and without preprocessing techniques for Chest X-ray report generation.	PO1, PO5
CC421.4, C2204.4, C22L3.2	Documenting preprocessing techniques, model evaluations, and BLEU score results collaboratively within the team.	PO10
CC421.5, C2204.2, C22L3.3	Presenting each phase of the project, including chest X-ray preprocessing, model predictions, and BLEU score evaluation, in a group setting.	PO10, PO11
C2202.2, C2203.3, C1206.3, C3204.3, C4110.2	Implementing and validating chest X-ray analysis models for healthcare applications with scope for future feature enhancements.	PO4, PO7
C32SC4.3	Designing a web interface to display chest X-ray predictions and assess model accuracy efficiently.	PO5, PO6

ABSRTACT

An automatic radiology report generation system is introduced with integrated image enhancement methods and a transformer model. Histogram Equalization, CLAHE, Exposure Fusion, and Gamma Correction method of image enhancement [8] was used to enhance the image quality of chest X-ray images. For cleaning text data, Word deconstruction, Character deletion followed by Lowercase conversion were done, then only BERT embeddings were applied considering contextual meaning. The model, trained on 9199 chest X-ray images, and 3973 medical reports incorporated the Multi-Head Attention to make the reports more coherent and relevant, provided better facilities for diagnosing and minimizing the efficiency time of the radiologists.

INDEX

LIST OF FIGURES

1.INTRODUCTION

Radiology is an essential field in medical diagnostics, providing crucial insights through imaging techniques such as X-rays, MRIs, and CT scans. With the increasing reliance on imaging for accurate diagnoses, radiologists face a significant rise in workload, reported to have increased by 26%. This surge in demand makes it challenging to maintain timely and precise report generation, impacting efficiency and patient care. The need for automated systems to assist in radiology workflows has become more evident to ensure accurate and standardized reporting[1].

A major challenge in radiology is the transformation of complex medical images into well-structured textual reports. [2]Traditional manual interpretation methods are time-consuming and susceptible to inconsistencies due to variations in human analysis. Therefore, there is a growing interest in developing automated techniques that can efficiently process medical images and generate structured reports.

This research introduces an advanced approach for automatic radiology report generation, focusing on enhancing the quality of input images using image processing techniques. The proposed model utilizes ChexNet, a convolutional neural network specifically designed for analyzing chest X-ray images, to extract essential visual features. To ensure the generated reports are structured and meaningful, the model incorporates preprocessing techniques such as Histogram Equalization (HE), Contrast-Limited Adaptive Histogram Equalization (CLAHE),[3] and Gamma Correction. These methods enhance image clarity, contrast, and detail visibility, making feature extraction more effective and contributing to accurate report generation.

The increasing demand for efficient and accurate radiology workflows has necessitated the development of automated systems that can aid in generating comprehensive medical reports. [4] Traditional radiology workflows heavily rely on manual interpretations by radiologists, which, although effective, come with challenges such as variability in reporting, time consumption, and the risk of diagnostic errors due to workload fatigue. The proposed research introduces an advanced transformer-based approach to automate radiology report generation while ensuring high-quality image enhancement and structured textual descriptions.

A crucial component of this system is ChexNet, a convolutional neural network (CNN) designed specifically for chest X-ray analysis. ChexNet has been widely adopted in radiology due to its ability to detect various lung diseases, including pneumonia, tuberculosis, and pulmonary edema. [5]By incorporating ChexNet into the model, the system can efficiently extract meaningful visual features, which serve as the foundation for generating structured radiology reports.

To ensure that the extracted features are accurate and interpretable, the research focuses on implementing image preprocessing techniques before feature extraction. The effectiveness of deep learning models in medical imaging largely depends on the quality of the input images. [6] Variations in contrast, noise, and brightness can obscure critical details in X-ray scans, leading to misinterpretations. To mitigate these issues, this research integrates Histogram Equalization (HE), Contrast-Limited Adaptive Histogram Equalization (CLAHE), and Gamma Correction as essential preprocessing steps.

By implementing a structured methodology for preprocessing and feature extraction, this approach aims to improve radiology workflows by reducing inconsistencies and enhancing the accuracy of medical reports. [7] With further advancements, this model can be expanded to include various imaging modalities, contributing to more efficient and reliable diagnostic practices.

Generating comprehensive and accurate radiology reports is a complex task that involves interpreting visual information and translating it into meaningful textual descriptions.[8] Traditional manual methods of report generation rely heavily on the expertise and experience of radiologists, making the process time-consuming and prone to variability. Different radiologists may interpret the same image differently, leading to inconsistencies in diagnosis and potential delays in patient treatment. Therefore, automated approaches to radiology report generation have gained significant attention, offering solutions to improve efficiency, accuracy, and standardization in medical imaging interpretation.

One of the primary challenges in automated radiology report generation is ensuring high-quality image analysis before report synthesis.[9] The quality of medical images varies due to differences in imaging conditions, patient positioning, and equipment limitations. Poor-quality images can obscure critical details, increasing

the risk of misinterpretation and diagnostic errors. To address these issues, advanced image enhancement techniques are required to improve image clarity and optimize feature extraction for better report generation.

This research focuses on a transformer-based model for automatic radiology report generation, emphasizing the importance of image enhancement techniques in improving input data quality.[10] The model utilizes ChexNet, a deep learning model designed for chest X-ray image analysis, to extract important visual features. To ensure meaningful and contextually relevant reports, BERT embeddings are employed to capture textual representations. Additionally, Multi-Head Attention mechanisms are integrated to align visual and textual features efficiently, enhancing the coherence of the generated reports.

Image preprocessing plays a vital role in improving diagnostic accuracy by refining input images before analysis. Several enhancement techniques are applied, including:

Histogram Equalization is a widely used technique in medical imaging for improving contrast by redistributing the intensity values of an image. In radiology, the intensity distribution of an X-ray image can often be uneven due to variations in radiation exposure and patient positioning**.** [1] HE ensures that the contrast is enhanced across the entire image, making finer details more visible.

In the context of chest X-ray analysis, HE helps in distinguishing lung opacities, nodules, and vascular structures, which are essential for detecting pulmonary diseases.This enhancement technique aids the deep learning model in extracting more distinguishable features, improving classification and segmentation performance.[2] However, a drawback of traditional Histogram Equalization is that it may over-amplify noise in areas where contrast variations are minimal. This necessitates the use of an adaptive method like CLAHE, which addresses the limitations of HE while preserving local details.

CLAHE is an advanced form of Histogram Equalization that enhances local contrast without over-amplifying noise. [11]Unlike HE, which applies contrast enhancement uniformly across the image, CLAHE divides the image into small sections (tiles) and applies contrast adjustments locally.This method prevents

overexposure of bright areas and ensures that subtle structures in the lungs and thoracic region are preserved.CLAHE has been shown to be particularly useful in low-dose X-ray images, where noise reduction is critical for accurate feature extraction.

By improving the visibility of critical structures in chest X-rays, CLAHE enables ChexNet to perform better in detecting abnormalities and classifying medical conditions.

Gamma Correction is a non-linear transformation applied to adjust brightness and contrast in images. X-ray images often suffer from variations in illumination due to differences in radiation exposure settings, patient positioning, and scanner type. Gamma Correction ensures that images are neither too dark nor too bright, which is crucial for feature extraction.

In chest X-ray analysis, Gamma Correction is particularly useful for highlighting soft tissue structures that might be less visible in low-contrast images.[5] The gamma value is adjusted based on the intensity distribution of the input image, ensuring that critical diagnostic information remains intact.

This preprocessing step enhances the quality of features extracted by ChexNet, leading to better performance in automatic report generation models**.** [3] By incorporating these preprocessing techniques, the model enhances image quality, ensuring that extracted features are more reliable for automated report generation. This approach reduces the likelihood of diagnostic errors and improves the overall effectiveness of the radiology workflow.

The integration of computational methods in radiology is expected to revolutionize medical imaging interpretation by providing standardized and efficient report generation. The proposed system offers several key benefits, including reduced workload for radiologists, enhanced diagnostic precision, and faster turnaround times for medical reports. Additionally, this approach minimizes inconsistencies in radiology interpretations, contributing to improved patient outcomes and streamlined healthcare processes.

In the future, the proposed model can be extended to other imaging modalities beyond chest X-rays, such as MRI and CT scans, further enhancing its applicability in diverse medical imaging scenarios. Additionally, integrating this automated system

with electronic health records (EHRs) could provide a more comprehensive diagnostic approach, allowing healthcare professionals to access and interpret patient histories alongside imaging results.

The increasing demand for radiology services, driven by an aging population and the rising prevalence of chronic diseases, highlights the critical need for improved efficiency in medical imaging. Radiologists are often overwhelmed with the sheer volume of images that need to be analyzed, which can lead to delays in diagnosis and potential errors. To address these challenges, leveraging advanced computational techniques, particularly in the areas of image enhancement and report generation, is essential. These methods can significantly reduce the time required to interpret medical images while maintaining high diagnostic accuracy, ultimately improving the overall efficiency of healthcare systems.

One promising approach involves the use of image enhancement techniques that can improve the quality of radiological images, making it easier for radiologists to identify key features in the images. Methods such as contrast adjustment, noise reduction, and edge detection can enhance the visibility of critical areas, allowing for more accurate and quicker interpretations. [18] Furthermore, these enhanced images can be fed into deep learning models to generate structured reports automatically, ensuring that the reports are consistent and accurate. Such advancements can greatly reduce the time radiologists spend on routine tasks, allowing them to focus more on complex and challenging cases that require their expertise.

As technology continues to evolve, the adoption of automated approaches in medical imaging will play a crucial role in enhancing diagnostic accuracy, reducing delays, and improving patient care. [15] By automating routine tasks like report generation, radiologists can dedicate more time to interpreting complex cases that require a higher level of expertise. Furthermore, the use of deep learning and transformer-based models can continuously improve as more data becomes available, leading to better performance over time. This not only improves the efficiency of radiology departments but also contributes to better patient outcomes by ensuring timely and accurate diagnoses.

2.LITERATURE SURVEY

Deep learning has revolutionized the field of medical image analysis, particularly in automated radiology report generation. Traditional radiology workflows rely on manual interpretation, which can be time-consuming and prone to variability among radiologists. Deep learning-based models, such as CNNs and LSTMs, enable automated and accurate disease detection from chest X-rays.[7] Studies have explored various architectures like CheXNet, which uses DenseNet for feature extraction, and sequence models like LSTM and Transformer-based models for text generation. Preprocessing techniques such as CLAHE and gamma correction have been used to enhance image quality, leading to improved classification accuracy and better report generation performance.

2.1 Deep Learning

Deep learning is a subset of machine learning that utilizes neural networks with multiple layers to extract hierarchical features from data. It excels in handling complex tasks such as image recognition, natural language processing, and medical diagnostics. Models like CNNs (Convolutional Neural Networks) [6] are commonly used for image-based tasks, while LSTMs (Long Short-Term Memory) and Transformer models handle sequential data, making them suitable for radiology report generation from medical images.

2.2 Applications of Deep Learning

Deep learning has significantly transformed healthcare, particularly in medical imaging, by enabling disease detection, segmentation, and automated report generation. Convolutional neural networks (CNNs) analyze medical images such as X-rays, MRIs, and CT scans with high accuracy, assisting in the early detection of conditions like cancer, pneumonia, and diabetic retinopathy. Deep learning models also facilitate precise segmentation of organs and tumors, improving diagnosis and treatment planning. Additionally, AI-powered systems can generate automated radiology reports by interpreting medical images, reducing the workload of healthcare professionals and enhancing diagnostic efficiency. In the finance sector, deep learning plays a crucial role in fraud detection, risk assessment, and algorithmic trading.

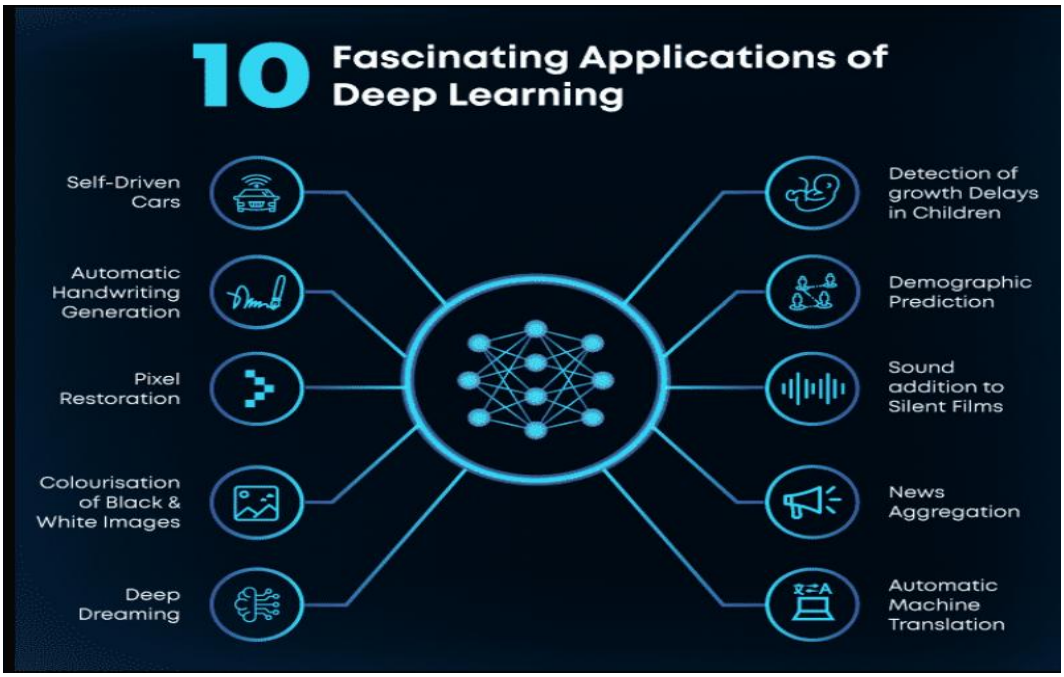

Fig 2.2.1 Applications of Deep Learning

2.3 Previous Studies & Findings

Several studies have explored the integration of deep learning techniques in automated radiology report generation, focusing on image processing, feature extraction, and natural language generation. Previous research highlights the effectiveness of models like ChexNet for chest X-ray analysis, BERT for contextual text generation, and various image enhancement techniques such as Histogram Equalization (HE) [5] and Contrast-Limited Adaptive Histogram Equalization (CLAHE) in improving diagnostic accuracy.

Rundo et al. (2020) review the application of nature-inspired algorithms in medical image analysis, emphasizing their role in enhancing biomedical data processing. The study highlights the effectiveness of swarm intelligence and evolutionary computing in improving image segmentation and classification. By integrating AI-driven approaches, the research showcases improvements in diagnostic accuracy. The findings underscore the potential of hybrid models combining deep learning with nature-inspired computing. Future research aims to explore further optimization of these models for clinical use.[1]

Li et al. (2021) introduce Mha-CoroCapsule, a novel multi-head attention-based capsule network for COVID-19 detection from chest X-ray (CXR) images. [16] Their model enhances feature extraction, leading to improved classification accuracy. The study demonstrates the advantages of capsule networks over traditional CNNs in

preserving spatial hierarchies. By incorporating attention mechanisms, the model refines medical image interpretation. The research highlights the potential of AI in early COVID-19 detection and diagnosis.[2]

Meedeniya et al. (2022) provide a systematic review of deep learning applications in chest X-ray analysis, particularly for disease detection. The study explores various architectures, including CNNs and generative models, and their role in automated diagnostics. The findings suggest that AI-driven solutions significantly reduce human error in radiological assessments. The review emphasizes the importance of standardized datasets for enhancing model performance. Future work suggests further research into explainability and robustness in deep learning applications.[3]

Demir (2021) presents DeepCoroNet, a deep LSTM-based model for automated COVID-19 detection using chest X-rays. By demonstrating the effectiveness of hybrid deep learning approaches, the research paves the way for future improvements in medical diagnostics. Future enhancements aim to improve model interpretability for clinical applications.[4]

Babar et al. (2021) evaluate encoder-decoder architectures for automated chest X-ray report generation, finding them less effective than baseline models. Their study identifies challenges in contextual understanding and consistency in generated reports. The research highlights the limitations of existing models in synthesizing coherent radiology descriptions. Recommendations include improving attention mechanisms and fine-tuning domain-specific language models. Future research focuses on enhancing linguistic coherence in AI-generated medical reports.[5]

Hira et al. (2021) propose a CNN-based approach for automatic COVID-19 detection from chest X-rays, demonstrating high efficiency in identifying infection patterns. Their model outperforms traditional radiological assessments in terms of speed and accuracy. The study emphasizes the significance of data augmentation techniques in improving model generalization. Results suggest that AI-assisted diagnostics can significantly reduce the burden on radiologists. Future directions include expanding the dataset to improve model robustness.[6]

Wijerathna et al. (2022) develop a CXR caption generation model based on CheXNet, a deep learning framework for automated medical reporting. Their approach leverages pre-trained features to generate meaningful and accurate radiology

descriptions. The study demonstrates improvements in text-image alignment, enhancing the reliability of AI-generated reports. Findings indicate the importance of contextual embeddings in medical language modeling. Future research focuses on incorporating clinical knowledge graphs for better report generation.[7]

Tsaniya et al. (2024) introduce an automatic radiology report generator using transformers and contrast-based image enhancement. Their study highlights the significance of pre-processing techniques in refining image quality. By improving image contrast, the model enhances the accuracy of AI-generated medical reports. Transformer-based architectures demonstrate superior performance in medical text synthesis. The research suggests integrating multimodal approaches for better diagnostic accuracy.[8]

Jonsson et al. (2022) propose parallel discrete convolutions for adaptive particle representations in medical imaging. Their study explores the computational efficiency of this method in large-scale image processing. Findings indicate that adaptive particle methods enhance diagnostic accuracy while maintaining high processing speeds. The research suggests that such techniques offer scalable solutions for real-time medical imaging. Future studies aim to integrate these methods with clinical decision-support systems.[9]

Xiao et al. (2022) utilize neural architecture search and multimodal imaging for intraoperative glioma grading. Their approach optimizes deep learning architectures for tumor classification in surgical settings. The study highlights the advantages of combining multiple imaging modalities for precise real-time diagnosis. AI-assisted imaging demonstrates significant potential in enhancing surgical decision-making. Future research focuses on developing real-time AI solutions for neurosurgery.[10]

Liu et al. (2021) investigate recognition-aware image processing to improve transfer learning in medical imaging. Their findings suggest that fine-tuned deep learning models outperform generic architectures in diagnostic accuracy. The research highlights the significance of domain adaptation in medical AI applications. Results indicate that optimizing pre-trained networks enhances model robustness in specialized medical tasks. Future work explores more adaptive learning techniques for clinical applications.[11]

Lu et al. (2014) propose an edge-guided dual-modality image reconstruction technique for improving medical imaging quality. Their method enhances edge

preservation, leading to improved visualization in complex scans. The study demonstrates how dual-modality approaches can combine different imaging techniques for better diagnostics. Findings suggest that real-time implementation of this technique can enhance medical imaging workflows. Future research focuses on optimizing computational efficiency for clinical integration.[12]

Su et al. (2020) explore emerging trends in quantum image representations for medical imaging. Their study highlights the potential of quantum computing in enhancing image storage and retrieval. Findings suggest that quantum-based models offer superior compression techniques for handling large-scale medical datasets. The research envisions a future where quantum AI revolutionizes medical imaging applications. [13]

Ye and Wang (2020) introduce an active contour segmentation method for medical imaging, improving boundary detection in radiological assessments. Their study emphasizes the importance of accurate segmentation in disease localization. Experimental results indicate superior performance compared to traditional segmentation methods. The research suggests that AI-driven segmentation techniques can improve diagnostic precision. Future studies aim to refine these methods for real-time medical applications.[14]

Raddar (2023) presents the Indiana University Chest X-ray dataset as a critical resource for deep learning research in radiology. Their dataset provides high-quality labeled data for training AI models in medical imaging. The study emphasizes the importance of publicly available datasets in advancing AI research. Researchers utilize this dataset for benchmarking diagnostic algorithms. Future work focuses on expanding and improving dataset annotations for better model training.[15]

Gamara et al. (2022) explore chest X-ray enhancement using CLAHE and Wiener filtering to improve deep learning preprocessing. Their study demonstrates how contrast enhancement and noise reduction significantly boost model performance. Findings suggest that high-quality input data leads to better AI-driven diagnostics. The research highlights the necessity of optimized preprocessing techniques in medical imaging. Future studies focus on real-time enhancement methods for clinical use.[16]

Yadav and Singhai (2024) propose an adaptive gamma correction technique for improving chest X-ray image contrast. Their method dynamically adjusts contrast

based on the severity of lung disease. Findings indicate enhanced visualization of abnormalities in radiological assessments. The study suggests that adaptive contrast adjustment techniques can refine medical image interpretation. Future work includes integrating AI-driven contrast optimization for automated diagnostics.[17]

Kumar et al. (2023) introduce an attention-guided CNN model for pneumonia detection in chest X-rays. Their approach enhances feature extraction, improving diagnostic accuracy. The study demonstrates that attention mechanisms significantly enhance model performance in complex medical imaging tasks. Findings suggest that AI-assisted diagnostics can reduce radiologist workload and improve efficiency. Future research explores integrating multi-scale feature fusion for better classification performance.[18]

3.SYSTEM ANALYSIS

3.1 EXISTING SYSTEM

DenseNet-121 is a convolutional neural network (CNN) architecture known for its effectiveness in image classification tasks. Unlike traditional CNNs, DenseNet-121 connects each layer to every other layer in a feed-forward fashion, promoting feature reuse and improving gradient flow. This architecture ensures that the network retains rich feature representations at every layer, enhancing its overall performance. In the context of this study, DenseNet-121 [1] is used as a pre-trained model to extract visual features from X-ray images. The model is fine-tuned for medical image captioning tasks by focusing on the lower layers, allowing it to capture critical features essential for generating detailed and accurate radiology reports.

ChexNet is another deep learning model specifically trained for detecting pneumonia in chest X-ray images. Based on a 121-layer DenseNet architecture, ChexNet has been optimized for recognizing patterns and abnormalities in chest X-rays. In the proposed report generation system, ChexNet [4] acts as a pre-trained encoder, providing initial weights for visual feature extraction. By leveraging its prior knowledge of chest X-ray images, ChexNet enhances the performance of the system, ensuring that the extracted features are relevant and useful for generating accurate medical reports. This approach significantly improves the accuracy and reliability of the system's output, particularly for tasks related to the detection of pneumonia and other chest-related conditions.

LSTM (Long Short-Term Memory) is a type of recurrent neural network (RNN) designed to model sequential data, making it well-suited for tasks that involve time-series or sequence generation. One of the key advantages of LSTM is its ability to address the vanishing gradient problem,[15] allowing it to learn long-range dependencies in data. In this paper, LSTM is used as the decoder component of the model, transforming the extracted visual features into coherent, text-based radiology reports. The LSTM network processes the sequential data from the visual domain and generates structured sentences that describe the findings from the X-ray images, making it a crucial part of the report generation process.

Adaptive Particle Representation (APR) is an innovative image representation technique that adjusts the sampling resolution based on the signal characteristics of the image. [9] This model is particularly useful for handling large, sparse images, such as those generated in fluorescence microscopy, where the images can have varying

levels of detail across different regions. APR dynamically adapts the resolution of the image based on the content, allowing for more efficient processing and better preservation of important features. This method ensures that computational resources are used effectively, particularly when dealing with complex medical images that require varying levels of detail for accurate analysis.

Discrete convolution operators are designed to work directly with APRs, marking a significant departure from traditional convolution methods that rely on uniform pixel grids. Traditional algorithms often revert to pixel-based representations, which can lead to inefficiencies in terms of memory usage and processing time. By operating directly on APRs, discrete convolution operators avoid these issues, improving both the efficiency and effectiveness of the convolution process. [12] This approach is particularly beneficial when working with large medical images, as it reduces computational overhead while maintaining high-quality results. The combination of APR and discrete convolution enables more efficient feature extraction and processing, contributing to faster and more accurate medical image analysis.

Parallel processing algorithms play a critical role in reducing computation times and handling large datasets efficiently. The convolution operations described in this paper are designed to take full advantage of parallel architectures, including CPUs and GPUs, enabling faster processing of medical images.

Graph-cut segmentation is a powerful technique used in image processing to partition an image into meaningful regions based on certain criteria, such as intensity or boundaries. Adapting graph-cut algorithms to work with APR enhances the flexibility of the model, enabling it to handle more complex segmentation tasks that go beyond simple convolution operations. This integration of graph-cut segmentation with APR highlights the potential for APR to be used in a wide range of image processing applications, expanding its utility beyond medical imaging to other fields requiring advanced image segmentation techniques.

3.1.1 DISADVANTAGES OF EXISTING SYSTEM

DenseNet-121, while offering efficient gradient flow and fewer epochs for training, still presents some challenges. One of the primary drawbacks is the time-consuming process of initial training or fine-tuning, especially due to its complexity. Even with its architecture designed to improve feature reuse, DenseNet-121 requires significant computational resources for training. Additionally, the model's performance is highly dependent on the quality of the input images. Noisy or low-

quality images can hinder the model's ability to effectively extract features, leading to suboptimal performance in generating accurate reports.

ChexNet, a model specifically trained for detecting pneumonia in chest X-rays, has its own limitations when applied to broader tasks. One of the main issues is its generalization capability. Since ChexNet was trained on a specific dataset like ChestX-ray14, it may not perform well when applied to other chest conditions not covered in the training set. This can restrict its ability to handle diverse patient populations or different imaging techniques. Additionally, ChexNet's performance is closely tied to the quality and quantity of the training data. If the data lacks diversity or is insufficiently annotated, the model’s ability to make reliable predictions can significantly decrease.

LSTM models, though effective for processing sequential data, face limitations in handling long sequences. Since LSTMs process data one time step at a time, they can be slower and less efficient than transformer-based models, particularly when the model needs to capture broader contexts or long-term dependencies within data. This sequential processing also makes LSTMs more memory and resource-intensive, which can be problematic for applications running on devices with limited computational resources. These constraints can hinder the scalability and efficiency of LSTM-based systems, especially in real-time applications.

The implementation of Adaptive Particle Representation (APR) comes with its own set of challenges. APRs require specific algorithms and data structures that differ significantly from conventional pixel-based methods. This added complexity can make it difficult to integrate APRs into existing systems, particularly for developers accustomed to traditional image processing techniques. Furthermore, many image processing algorithms are designed for uniform pixel grids, and adapting them to work with the non-uniform sampling patterns of APRs can lead to accuracy and effectiveness issues. Optimizing the performance of these algorithms when applied to APRs is not always straightforward and requires careful adjustments.

Another challenge lies in the performance of GPUs when processing APRs. Although GPUs are designed for parallel processing, they are typically optimized for working with uniform data structures like regular pixel grids. When processing the sparsely distributed data inherent in APRs, data access patterns become more complicated, limiting the potential performance gains. This mismatch between the structure of APRs and GPU optimization may reduce the efficiency of the system.

3.2 PROPOSED SYSTEM

The proposed system for automatic radiology report generation leverages advanced methodologies in image enhancement and natural language processing to produce coherent radiology reports from chest X-ray images. Central to this system are two significant components: ChexNet for image feature extraction and a transformer model, augmented by Long Short-Term Memory (LSTM) networks, for text generation.

To enhance the quality of X-ray images, the system employs several sophisticated image enhancement techniques. These include Histogram Equalization, Contrast Limited Adaptive Histogram Equalization (CLAHE), Exposure Fusion, and Gamma Correction. Among these, gamma correction was found to yield the best results in terms of image clarity and detail, crucial for accurate feature extraction. These methods work collectively to improve contrast and brightness, making significant features in the images more discernible and thus facilitating better analysis by the subsequent processing algorithms.

Once the images are enhanced, ChexNet is utilized to extract visual features effectively. This model is designed to identify critical visual patterns associated with various medical conditions present in the chest X-rays. Simultaneously, for the text generation component, [13] BERT embeddings are employed to capture the contextual meaning of the language in medical reports. The integration of BERT provides a nuanced understanding of medical terminology and phrasing, which is essential for generating accurate and readable reports.

The system's architecture incorporates Multi-Head Attention, allowing it to focus on multiple aspects of the visual and textual data simultaneously, thus enhancing the coherence and relevance of the generated reports.

Furthermore, the system utilizes a well-curated dataset consisting of 9,199 chest X-ray images and 3,973 corresponding radiology reports, sourced from the Indiana University Hospital Link (IUHL) database. This dataset's diversity facilitates rigorous training and enhances the model's ability to generalize across different types of cases and diagnostic challenges. The integration of preprocessing steps—such as character deletion, word deconstruction, and normalization—ensures that the textual data input into the model is clean and conducive to achieving higher-quality outputs.

In summary, the proposed system integrates image enhancement, feature extraction, and contextual text generation into a cohesive workflow that aims to automate and optimize the creation of radiology reports. It addresses existing

bottlenecks in radiology, enhancing both diagnostic precision and operational efficiency.

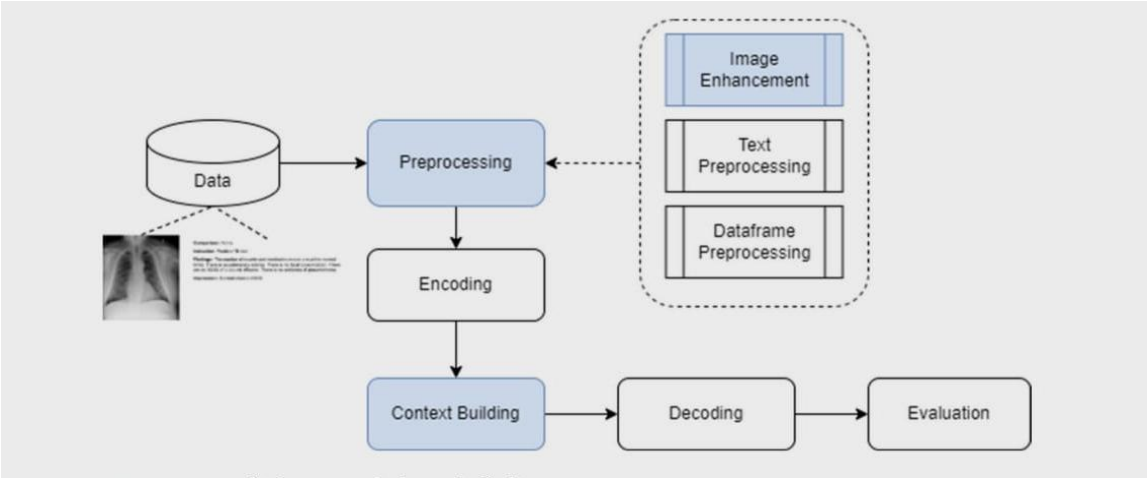

Fig 3.2 Flow chart of Proposed system

The above figure presents a data processing pipeline, illustrating the transformation of raw data into a structured output through multiple stages. The flow begins with a Data repository that can store various types of information, including text and images. A sample image with corresponding text metadata is depicted, indicating that the system might be dealing with medical or image-based data. The next step is Preprocessing, where raw data undergoes cleaning and enhancement. This stage includes Image Enhancement for refining image quality, Text Preprocessing for structuring textual information, and Dataframe Preprocessing for organizing tabular data. These preprocessing techniques help standardize the input, ensuring that the subsequent stages receive well-structured and meaningful data.

Following preprocessing, the pipeline moves to Encoding, which likely converts the processed data into a suitable numerical representation for computational tasks. This encoded data is then passed to the Context Building stage, which could involve deep learning or machine learning models to extract meaningful insights. After context is built, the Decoding phase translates the processed information back into a human-readable or interpretable format. The final Evaluation stage assesses the effectiveness of the entire process, ensuring that the output meets predefined accuracy and quality standards. This structured workflow suggests a comprehensive approach to handling complex datasets, particularly in areas like medical imaging or natural language processing.

3.3 FEASIBILITY STUDY

The feasibility of implementing an automated radiology report generation system depends on several critical factors, including technical viability, resource availability, economic considerations, and system integration. The proposed system utilizes deep learning models for chest X-ray analysis, image preprocessing techniques, and natural language processing for structured report generation. This feasibility study assesses whether the system can be efficiently developed, deployed, and used in real-world medical environments.

3.3.1. Technical Feasibility

The technical feasibility of this system is supported by the availability of advanced deep learning frameworks such as TensorFlow and PyTorch, which enable efficient training and deployment of ChexNet for feature extraction and BERT for report generation. [16] The system's development environment, Google Colab, provides GPU and TPU acceleration, eliminating the need for expensive hardware and ensuring efficient model training. Additionally, the use of Flask for web deployment and OpenCV for image preprocessing allows seamless integration of model inference with real-time image analysis. Since all required technologies are open-source and widely used in AI-driven medical applications, the system is technically feasible and scalable.

3.3.2. Operational Feasibility

From an operational perspective, the system is designed to enhance radiology workflows by automating report generation, thereby reducing radiologists' workload and improving diagnostic consistency. The web-based interface, developed using HTML, CSS, and Flask, ensures ease of access for medical professionals through a browser-based platform. The system can process X-ray images uploaded by users and return structured reports in real-time, significantly improving efficiency in clinical settings. Furthermore, preprocessing techniques such as Histogram Equalization (HE) and CLAHE enhance image quality, ensuring accurate feature extraction and diagnosis. Since the system can be deployed in hospitals, research centers, and diagnostic laboratories, it meets the operational feasibility criteria.

3.3.3. Economic Feasibility

The economic feasibility of this project is strengthened by its reliance on cost-effective, open-source software tools. The use of Google Colab for training eliminates the need for dedicated high-performance computing hardware, reducing initial investment costs. Additionally, cloud-based storage solutions such as Google Drive

help manage large datasets without requiring expensive data management infrastructure. Since Flask and OpenCV are free-to-use frameworks, the system minimizes licensing and maintenance costs. Compared to traditional manual radiology reporting methods, this system provides a cost-efficient alternative by reducing report turnaround time and improving diagnostic accuracy, making it financially viable for healthcare institutions.

3.3.4. System Integration Feasibility

The proposed system can be seamlessly integrated into existing hospital infrastructures and radiology workflows. The web-based approach ensures that radiologists can access the system without installing additional software, making deployment easier.

The feasibility study indicates that the proposed automated radiology report generation system is technically, operationally, and economically viable. With the use of deep learning frameworks, cloud-based training environments, and open-source web technologies, the system can be efficiently implemented in clinical settings. Its ability to improve diagnostic workflows, reduce radiologists' workload, and provide cost-effective solutions makes it a practical and scalable approach for modern medical imaging applications.

3.4 Using COCOMO Model

The Constructive Cost Model (COCOMO) is a widely used software estimation model that helps predict the effort, time, and cost required for software development. It classifies projects into three modes: Organic, Semi-Detached, and Embedded, based on complexity, team experience, and constraints. Since our automated radiology report generation system is being developed by a small team of 3 members, it falls under the Organic Mode, which is suitable for small to medium-sized projects with experienced developers and minimal complexity.

4.SYSTEM REQUIREMENTS

4.1 Software Requirements

Developing an automated radiology report generation system requires a carefully chosen software stack to support deep learning, image processing, NLP, web development, and deployment. Python is the ideal programming language due to its extensive AI and medical imaging libraries, such as TensorFlow, PyTorch, OpenCV, NumPy, Pandas, and NLTK, ensuring seamless integration with cloud services and databases. For deep learning, TensorFlow and PyTorch are the most suitable frameworks, offering GPU acceleration and support for pre-trained models like ChexNet and BERT. OpenCV is the preferred image processing library, providing essential functions like Histogram Equalization (HE), CLAHE, and Gamma Correction to enhance medical images before analysis. NLP techniques are necessary for generating structured and meaningful reports, with BERT embeddings ensuring context-aware text generation and NLTK handling text preprocessing tasks.

To enable real-time interaction, Flask is the preferred web framework, allowing users to upload X-ray images, process them, and generate diagnostic reports efficiently. Google Colab serves as the best training environment, offering free GPU and TPU access for deep learning model development and integration with Jupyter Notebooks for interactive coding. The final system is deployed via a web interface built with HTML, CSS, and JavaScript, ensuring accessibility across browsers and devices for seamless radiologist interaction. By combining Python, TensorFlow/PyTorch, OpenCV, Hugging Face Transformers, Flask, and Google Colab, the project ensures efficient model training, accurate radiology report generation, and practical deployment in real-world medical applications.

4.2 HARDWARE REQUIREMENTS

The hardware requirements for implementing and testing this project locally are relatively modest, though for training deep learning models, a GPU is preferred. Since you used an HP i3 laptop, here are the relevant minimum and recommended specifications:

Minimum Requirements (for local execution & small datasets):

- Processor: Intel Core i3 (2.1 GHz or above)
- RAM: 8 GB

- Hard Disk: 500 GB HDD or SSD
- Graphics: Integrated Intel HD Graphics (sufficient for basic visualization, not
- ideal for training)
- Operating System: Windows 11 or higher
- Internet Connectivity: Required for Google Colab access

Recommended (for faster local execution or larger datasets):

- Processor: Intel Core i5 or i7
- RAM: 16 GB
- Storage: 512 GB SSD
- Graphics: Dedicated GPU (e.g., NVIDIA GTX 1650 or higher)
- Cooling: Laptop cooling pad if performing extended training sessions

4.3 REQUIREMENT ANALYSIS

The requirement analysis for the proposed automatic radiology report generation system involves evaluating both functional and non-functional requirements to ensure efficiency, reliability, and usability. The primary functional requirement is the successful capture and enhancement of chest X-ray images using advanced image processing techniques like Histogram Equalization, CLAHE, and Gamma Correction to improve clarity and contrast. Robust text processing is also essential, integrating BERT embeddings for natural language understanding and Multi-Head Attention mechanisms [17] to ensure accurate and context-aware report generation. The user interface must be intuitive, allowing radiologists to seamlessly upload images, view enhancements, and access generated reports, while maintaining a streamlined experience that integrates smoothly into their workflow.

Non-functional requirements focus on performance, reliability, and security. The system must efficiently process large volumes of data, ensuring fast image enhancement and report generation without compromising output quality. Reliability is crucial, as clinicians rely on accurate reports for diagnosis, necessitating rigorous testing to minimize errors in image analysis and text generation. Additionally, security measures must protect patient data, ensuring compliance with healthcare regulations and maintaining data privacy. Addressing these requirements holistically will provide a solid foundation for the system, making it both effective and practical for medical professionals.

4.4 SOFTWARE

To develop an automated radiology report generation system, a well-structured software stack is essential. The system requires deep learning frameworks for model training, image processing libraries for enhancement, natural language processing tools for generating structured reports, and web development technologies for deployment. The software choices ensure seamless integration of image analysis and text generation, enabling radiologists to efficiently process and interpret chest X-ray images. The following sections provide a detailed description of each software component used in this project.

4.5 SOFTWARE DESCRIPTION

Python

Python is the primary programming language used in this project due to its extensive support for machine learning, deep learning, and natural language processing. It offers a vast ecosystem of libraries such as TensorFlow, PyTorch, OpenCV, and NLTK, making it suitable for handling medical image processing, feature extraction, and report generation. Additionally, Python's flexibility allows for seamless integration with cloud platforms, databases, and web applications, ensuring an efficient workflow for radiology automation

Google Colab

Google Colab serves as the primary development environment for training deep learning models. It provides free access to GPUs and TPUs, significantly reducing training time. With built-in Jupyter Notebook support, Colab allows for interactive coding, real-time visualization of model performance, and seamless integration with cloud storage solutions like Google Drive. This makes it highly suitable for handling large medical imaging datasets such as the Indiana University Hospital Link (IUHL) dataset.

OpenCV

Image preprocessing is a crucial step in medical image analysis. OpenCV is used to enhance chest X-ray images by applying techniques such as Histogram Equalization (HE) for contrast enhancement, Contrast-Limited Adaptive Histogram Equalization (CLAHE) for noise reduction, and Gamma Correction for brightness adjustment. These enhancements ensure better feature extraction and improve the accuracy of deep learning models.

Flask

To deploy the trained deep learning model and enable user interaction, Flask is used as the backend web framework. Flask allows users to upload chest X-ray images, process them using the trained model, and receive structured radiology reports. It supports RESTful API development and can be deployed on cloud platforms like AWS, Google Cloud, or Heroku, making it scalable for hospital and research use.

Web Browser

The final application is designed to be accessible through a web browser, eliminating the need for additional software installation. The system can be accessed via Google Chrome, Mozilla Firefox, Microsoft Edge, or Safari, ensuring ease of use in hospital environments. A browser-based interface ensures secure and remote access for radiologists and healthcare professionals.

5.SYSTEM DESIGN

5.1 SYSTEM ARCHITECTURE

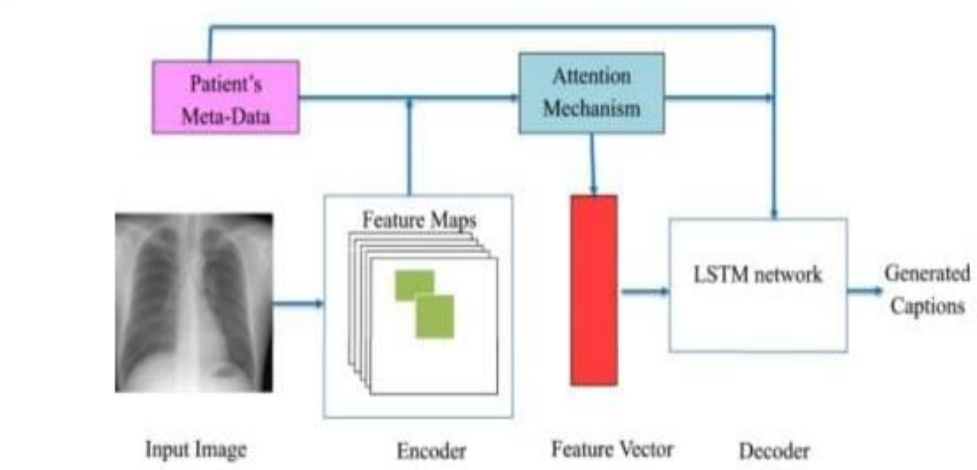

Fig: 5.1.1 Model Architecture

5.1.1 Dataset

The dataset utilized for training and evaluating the automatic radiology report generation system comprises 9,199 chest X-ray images and 3,973 corresponding radiology reports sourced from the Indiana University Hospital Link (IUHL) database. This dataset is notable for its richness in disease prevalence and variety, encompassing a wide spectrum of conditions ranging from minimal lung field opacity to significant pathologies. The IUHL database is widely recognized in the research community for its utility in developing machine learning models, offering a substantial and diverse collection of patient records that serve as a benchmark for automatic report generation systems. To address potential dataset bias, the system employs techniques such as bootstrapping with normal report undersampling and over-representation of under-represented findings. This approach ensures that the model learns effectively from a balanced representation of various health conditions present in the chest X-rays, improving its robustness and accuracy.Dataset link is below :

https://www.kaggle.com/datasets/raddar/chest-xrays-indiana-university

Aspect	Details
Dataset Name	Indiana University Hospital Link (IUHL) Database
Number of X-ray Images	9,199
Number of Text Radiology Reports	3,973
Content Richness	Rich in disease prevalence and variety, with many co-occurrences
Purpose	Benchmark for developing and evaluating automatic text report generation systems
Challenges	Sub-categorization of reports into Major Categories/Diseases
Use in Research	Widely adopted in the research community, ideal for developing ML models due to size and diversity

5.1.2 Preprocessing

The preprocessing phase in the automatic radiology report generation system is crucial for enhancing the quality of chest X-ray images and ensuring accurate report generation. This phase involves several key steps aimed at improving both the visual data and the textual descriptions associated with the images.

1. Image Preprocessing: The preprocessing of images begins with various enhancement techniques designed to improve the quality of the input data. The following methods are employed:

- **Histogram Equalization (HE):** This technique enhances the contrast of the images by redistributing the intensity values. [9] It effectively stretches the range of intensity values, making features in the images more distinguishable.
- **Contrast Limited Adaptive Histogram Equalization (CLAHE):** Unlike standard histogram equalization, CLAHE operates on small regions (tiles) of the image, enhancing local contrast while preventing noise amplification. This method is particularly useful in medical imaging, where subtle differences in tissue density are critical for diagnosis.
- **Gamma Correction:** This nonlinear image adjustment technique modifies the brightness and contrast of images. By applying adaptive gamma correction, the system can enhance critical features, ensuring that important details are more visible for accurate diagnosis.
- **Exposure Fusion Framework (EFF):** This method integrates multiple images taken at different exposure levels into a single composite image. The result is an image that retains the best attributes from all incorporated images, improving feature recognition and detail visibility.

- **Normalization:** Normalization of pixel intensity values is performed to avoid significant variations in brightness and contrast across samples. This step ensures that the images are standardized, facilitating better feature extraction.
- **Filtering Operations:** Noise reduction is achieved through filtering operations, which clean the images by removing unwanted artifacts. This step is essential for improving the quality of the input data before feature extraction.

2. Text Data Preprocessing: In addition to image preprocessing, the textual data associated with the radiology reports undergoes several cleaning and enhancement steps:

- **Word Deconstruction:** This process involves breaking down words into smaller components to enhance feature extraction. By identifying specific and similar descriptions, the model can better understand the context of the text.
- **Character and Number Deletion:** Unnecessary characters and numbers are removed from the text data to streamline the input. This cleaning step ensures that only relevant information is retained for analysis.
- **Lowercasing:** All text is converted to lowercase to reduce variation and maintain consistency in the data. This step helps in standardizing the input for further processing.

Medical Report Filtering: The text data is filtered to ensure that only relevant medical reports are used for training the model. This filtering process enhances the quality of the training data.

By integrating both image and text preprocessing techniques, the overall quality of input data is significantly enhanced, leading to more accurate and reliable deep learning models. Image enhancement methods ensure that critical features are well-preserved and distinguishable, improving diagnostic accuracy in medical imaging applications. Simultaneously, text preprocessing refines the structured data from radiology reports, ensuring that only relevant and meaningful information is utilized for model training. The combination of these preprocessing steps not only reduces noise and inconsistencies but also facilitates better feature extraction. Properly preprocessed data leads to more robust models capable of making precise predictions, assisting healthcare professionals in making more informed decisions, and enhancing patient outcomes.

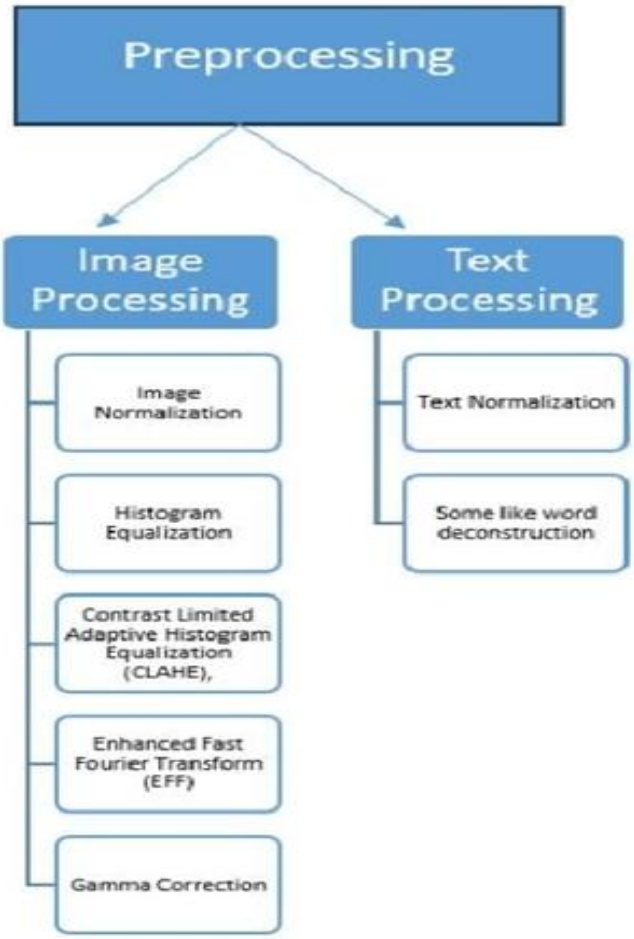

Fig 5.1.2 Preprocessing

5.1.3 Models

The system architecture integrates multiple advanced models, namely ChexNet and BERT, alongside Long Short-Term Memory (LSTM) networks, to facilitate the effective generation of radiology reports from X-ray images.

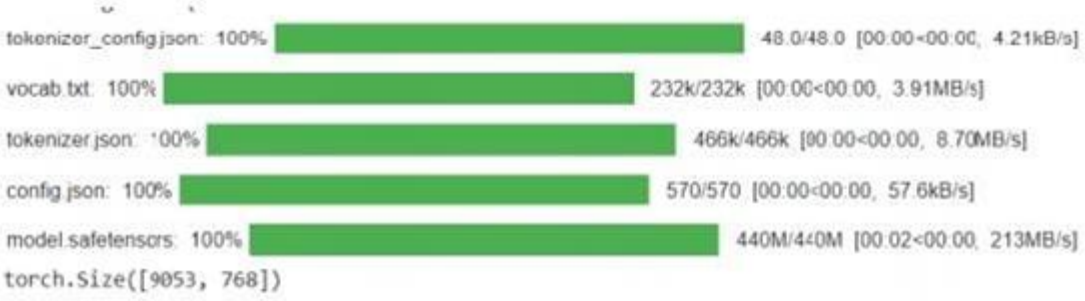

Fig 5.1.3 BERT Embedding

ChexNet is a convolutional neural network (CNN)[14] specifically designed to process chest X-ray images and is proficient in extracting visual features associated with various pathologies, including pneumonia and other diseases. By employing ChexNet, the system can accurately localize multiple conditions within the X-rays, thereby providing the foundational visual information necessary for report generation.

The BERT model (Bidirectional Encoder Representations from Transformers) plays a crucial role in understanding and encoding the textual information from radiology reports. BERT's strength lies in its ability to comprehend the context of words within sentences, which is essential for generating precise descriptions based on extracted image features. To enhance the interaction between visual and textual data, Multi-Head Attention mechanisms are employed. These mechanisms allow the model to focus on various elements of the input data concurrently, promoting better learning of the correlations between visual and textual contexts.

LSTM networks are employed to structure the overall report generation process, managing the sequential flow of information derived from the features extracted by ChexNet and the contextual embeddings provided by BERT. The LSTM's design—including input, output, [18] and forget gates—facilitates the retention of contextual information, enabling the generation of coherent and accurate medical reports. This multi-model approach effectively bridges the gap between visual analysis and natural language processing, culminating in a robust system capable of producing high-quality and informative radiology reports.

The architecture of the model is designed to integrate the extracted features from both images and text, ensuring a comprehensive understanding of medical data. A transformer-based architecture is employed, leveraging Multi-Head Attention mechanisms to facilitate the interaction between visual and textual features effectively. Additionally, positional encodings and self-attention layers help maintain contextual consistency, allowing the model to generate structured and meaningful diagnostic summaries. This fusion of multimodal data enhances the coherence, accuracy, and relevance of the generated reports, ultimately improving the decision-making process for healthcare professionals.

Fig 5.1.4 Histogram Equalization

Fig 5.1.5 CLAHE

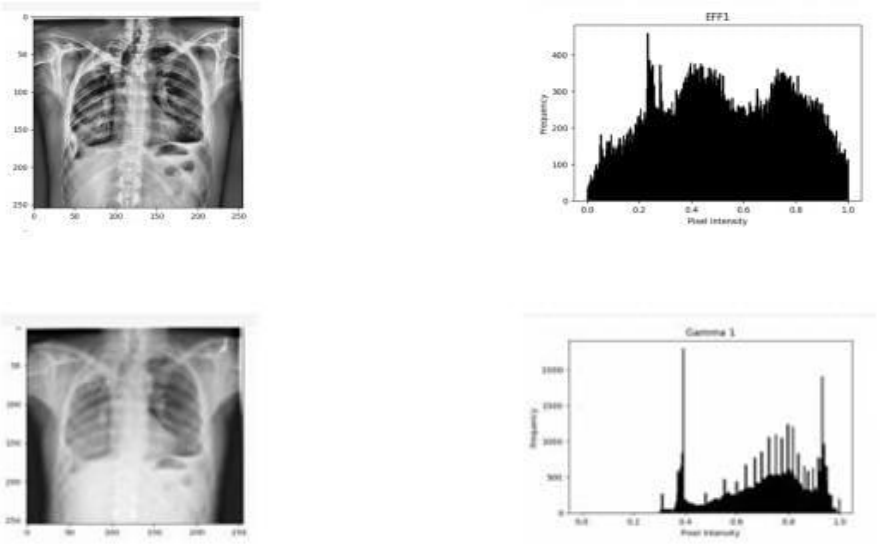

Fig 5.1.6 EFF,Gamma Correction

Multi Head Attention (MHA) : The Multi-Head Attention model is a key component of transformer architectures, enabling the model to focus on different parts of the input sequence simultaneously. [11]It operates by creating multiple attention heads, each learning distinct representations of the input data. Each head computes attention scores based on query, key, and value vectors, allowing the model to capture various relationships and dependencies within the data. This mechanism is particularly effective in tasks like natural language processing and image captioning, improving contextual understanding and coherence.

LSTM (Long Short-Term Memory) : LSTM decoder is a crucial component in sequence-to-sequence models, particularly in tasks like natural language processing and automatic report generation. It processes input sequences, maintaining a memory cell that captures long-range dependencies and contextual information. LSTM decoder enhances the quality of generated text, making it suitable for complex narrative tasks.

5.2 Modules

Comparison Analysis

The radiology report generation system is built using a combination of deep learning models that extract visual features from chest X-ray images and generate descriptive medical reports. The approach involves integrating CheXNet (a variant of DenseNet-121) for feature extraction, LSTM (Long Short-Term Memory networks) for sequential text generation, and Multi-Head Attention (MHA) [7] to improve the quality of the generated reports. Different versions of the model are tested with various image enhancement techniques to optimize the feature extraction process. The following sections describe the individual model combinations and their effectiveness.

CheXNet + LSTM

The basic model pipeline starts with CheXNet, a pre-trained deep learning model designed for medical image classification. It processes chest X-ray images and extracts high-level features that are crucial for detecting abnormalities. The extracted features, which are 18-dimensional vectors, are then passed into an LSTM-based sequence model. LSTM is a type of recurrent neural network (RNN) that is well-suited for processing sequential data, making it ideal for generating radiology reports based on the extracted image features. However, while this combination performs decently, it struggles with extracting finer details from low-contrast images.

CheXNet + LSTM with Histogram Equalization (HE)

To improve contrast and feature clarity, Histogram Equalization (HE) is applied to X-ray images before feeding them into CheXNet. HE enhances the overall brightness distribution in images, making pathological features more distinguishable. The CheXNet model then extracts features from these enhanced images, which are passed into the LSTM model for text generation.[14] This approach results in a slight improvement in BLEU scores compared to the base CheXNet-LSTM model, as the

enhanced images provide clearer representations of abnormalities. However, HE sometimes over-enhances regions, leading to false feature amplification in certain cases.

CheXNet + LSTM with Contrast Limited Adaptive Histogram Equalization (CLAHE)

To mitigate the limitations of HE, Contrast Limited Adaptive Histogram Equalization (CLAHE) is introduced. CLAHE improves local contrast in images while preventing over-amplification of noise, making it more effective for medical imaging applications. The CheXNet model processes these CLAHE-enhanced images to extract features, and the LSTM network generates corresponding reports. This model combination achieves the best BLEU score, as it retains crisp feature details while avoiding excessive contrast enhancement. The generated reports are more accurate and detailed, making this the most effective approach among the tested models.

CheXNet + LSTM + CLAHE + Multi-Head Attention (MHA)

To further enhance the report generation process, Multi-Head Attention (MHA) is incorporated alongside CheXNet-LSTM-CLAHE.[8] Attention mechanisms help the model focus on relevant parts of the extracted features while generating text, improving the quality and coherence of the generated reports. In this model, the CheXNet-extracted features undergo transformation through a linear projection layer to align with the LSTM's hidden dimensions. The Multi-Head Attention module then helps the LSTM focus on critical features, leading to more structured and medically relevant reports. This final model performs exceptionally well, producing high BLEU scores and coherent, contextually accurate radiology descriptions.

5.3 UML DIAGRAMS

1. Sequence Diagram

The sequence diagram outlines the interaction and flow of events in the system:

1. User uploads a chest X-ray via the web interface.
2. The web interface sends the image to the Flask backend for processing.

3. The Flask backend forwards the image to Image Processing (OpenCV) for enhancement (HE, CLAHE, Gamma Correction).
4. The preprocessed image is passed to ChexNet for feature extraction.
5. ChexNet extracts features and sends them to BERT for generating a text-based report.
6. BERT generates the report and sends it to the Flask backend.
7. The Flask backend returns the report to the web interface.
8. The web interface displays the final report to the user.

This diagram shows the complete process from image upload to report generation.

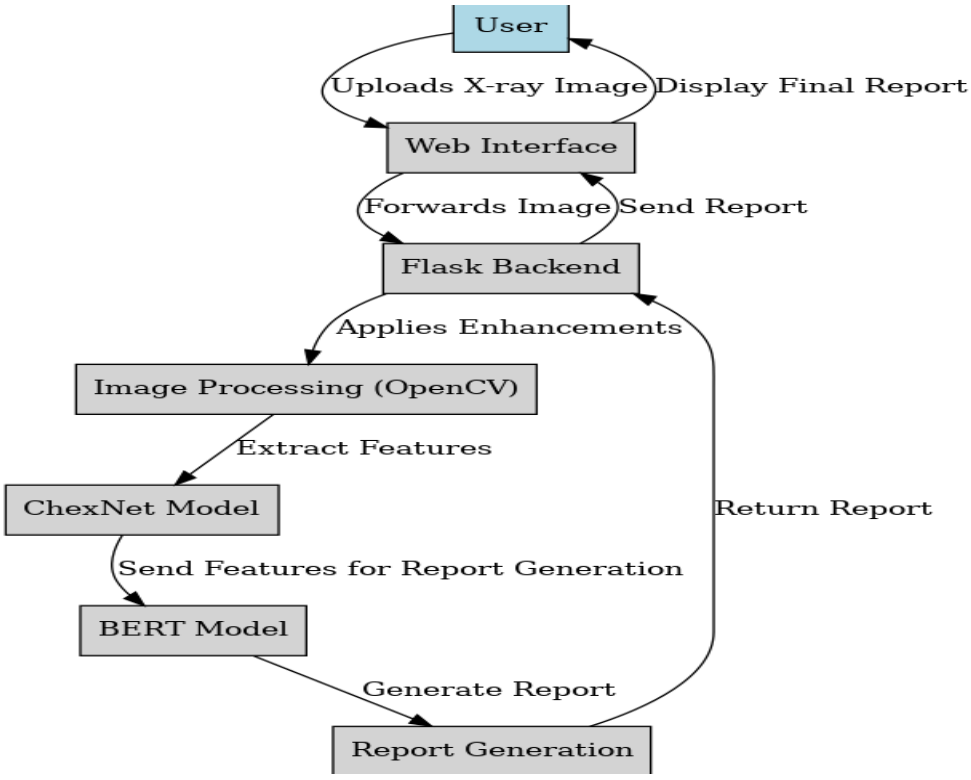

Fig 5.3.1 Sequence Diagram

2. Use Case Diagram

The use case diagram illustrates actors and their interactions:

- User (Radiologist/Medical Professional): Uploads X-ray images, views, and downloads reports.
- System Administrator: Manages user access and system settings.

- AI Model (ChexNet & BERT): Processes images and generates reports.

Functional Use Cases:

- Upload Image: User uploads an X-ray.
- Preprocess Image: OpenCV enhances the image.
- Feature Extraction: ChexNet extracts features.
- Generate Report: BERT creates a structured report.
- View/Download Report: User reviews and saves the report.
- Manage System: Admin handles configurations.

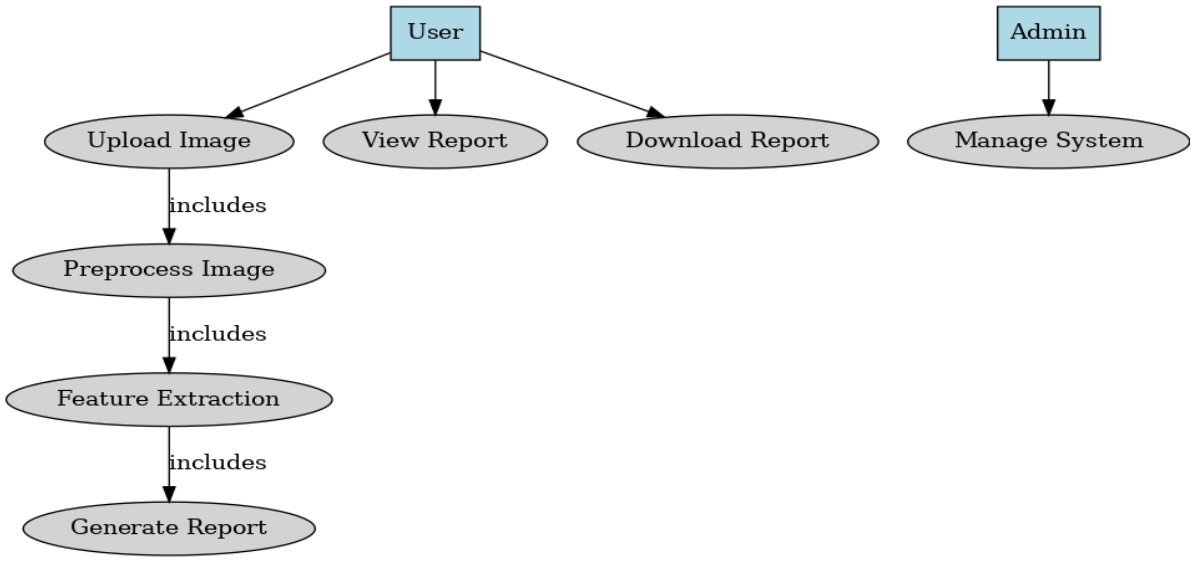

Fig 5.3.2 UseCase Diagram

3. Class Diagram

The class diagram represents the system's structure, including key classes and their relationships:

- User Class: Represents radiologists with attributes (userID, name, role) and methods (login(), uploadImage(), viewReport()).
- ImageProcessor Class: Preprocesses images using methods like HE, CLAHE, and Gamma Correction, with attributes imageID and preprocessingType.
- AIModel Class: Extracts features and generates reports.

- ChexNet Class (Inherits AIModel): Analyzes X-rays.
- BERTModel Class (Inherits AIModel): Generates text-based reports.

- Report Class: Manages reports with attributes (reportID, reportText, timestamp), and provides methods like saveReport() and downloadReport().
- SystemAdmin Class: Manages system settings and users.

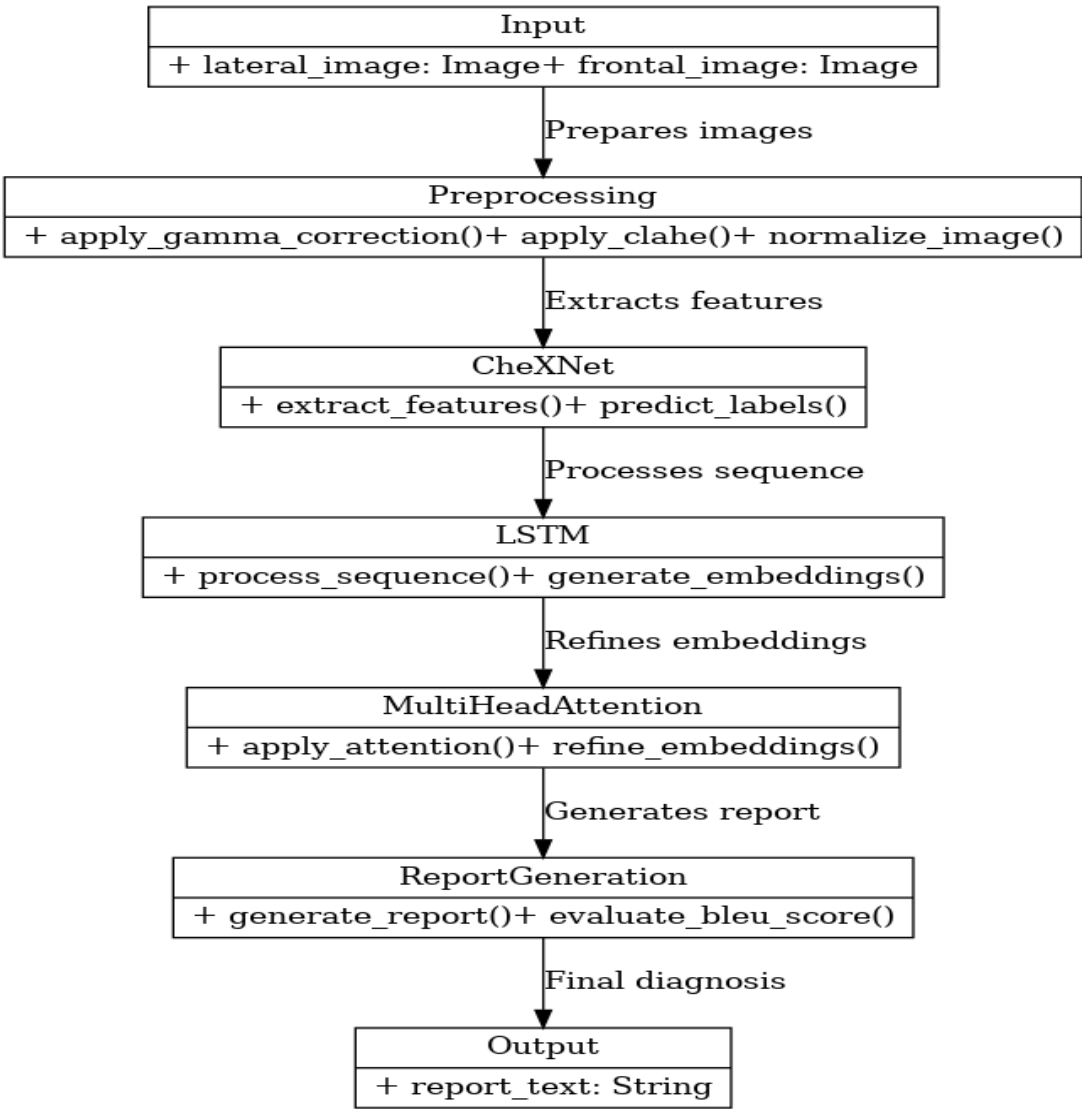

Fig 5.3.3 Class Diagram

6.IMPLEMENTATION

6.1 Model Implementation

```
#CheXNet + LSTM + CLAHE + MHA

def chexnet_lstm_mha_pipeline(images_tensor, hidden_size=256, num_layers=2, num_heads=8):

    chexnet_model = DenseNet(weights="densenet121-res224-chex")

    chexnet_model.eval()

    with torch.no_grad():

        chexnet_output = chexnet_model(images_tensor)

    lstm_decoder = LSTMDecoder(input_size=chexnet_output.shape[1], hidden_size=hidden_size, num_layers=num_layers)

    lstm_output = lstm_decoder(chexnet_output.unsqueeze(1))

    mha_module = MultiHeadAttentionModule(embed_dim=hidden_size, num_heads=num_heads)

    attn_output = mha_module(lstm_output, lstm_output, lstm_output)

    return attn_output
```

6.2 Coding

```
# Step 1: Mount Google Drive

from google.colab import drive

drive.mount('/content/drive')

# Step 2: Read the ag8 folder

import os

path = '/content/drive/My Drive/ag8'

print(os.listdir(path))
```

```
# Step 3: Read images from the folder
image_path = '/content/drive/My Drive/ag8/images'
for filename in os.listdir(image_path):
    print(filename)
# Step 4: Resize all images in images_normalized to 255x255
from PIL import Image
normalized_path = '/content/drive/My Drive/ag8/images_normalized'
os.makedirs(normalized_path, exist_ok=True)
for filename in os.listdir(image_path):
    if filename.endswith('.jpg') or filename.endswith('.png'):
        img = Image.open(os.path.join(image_path, filename))
        img = img.resize((255, 255))
        img.save(os.path.join(normalized_path, filename))
# Step 5: Convert resized images to NumPy arrays
import numpy as np
image_arrays = []
for filename in os.listdir(normalized_path):
    if filename.endswith('.jpg') or filename.endswith('.png'):
        img = Image.open(os.path.join(normalized_path, filename))
        img_array = np.array(img)
        image_arrays.append(img_array)
# Step 6: Normalize the images
normalized_images = [img_array / 255.0 for img_array in image_arrays]
# Step 7: Merge CSV files
import pandas as pd
```

```
df1 = pd.read_csv('/content/drive/My Drive/ag8/indiana_projections.csv')

df2 = pd.read_csv('/content/drive/My Drive/ag8/indiana_reports.csv')

merged_df = pd.concat([df1, df2], ignore_index=True)

merged_df.to_csv('/content/drive/My Drive/ag8/merged_file.csv', index=False)

# Step 8: Process CSV data

from sklearn.preprocessing import MinMaxScaler, OneHotEncoder

merged_df = pd.read_csv('/content/drive/My Drive/ag8/merged_file.csv')

# Normalize 'uid'

scaler_uid = MinMaxScaler()

merged_df['uid'] = scaler_uid.fit_transform(merged_df[['uid']])

# One-Hot Encode 'projection'

encoder = OneHotEncoder(handle_unknown='ignore', sparse=False)

encoded_projection = encoder.fit_transform(merged_df[['projection']])

# Convert filenames

def process_text(text):

    text = text.replace(' ', '_')

    text = ''.join(char for char in text if char.isalpha())

    return text.lower()

merged_df['filename'] = merged_df['filename'].astype(str).apply(process_text)

# Combine data

encoded_projection_df = pd.DataFrame(encoded_projection,
columns=encoder.get_feature_names_out(['projection']))

merged_df = pd.concat([merged_df.drop(columns=['projection']),
encoded_projection_df], axis=1)

# Step 9: Remove NaN/null values

merged_df.dropna(inplace=True)
```

```
# Convert to NumPy array
combined_array = merged_df.to_numpy()
# Step 10: Split data into training, validation, and test sets
from sklearn.model_selection import train_test_split
# Split images
train_images, temp_images = train_test_split(normalized_images, test_size=0.2, random_state=42)
val_images, test_images = train_test_split(temp_images, test_size=0.5, random_state=42)
# Split CSV data
train_data, temp_data = train_test_split(combined_array, test_size=0.2, random_state=42)
val_data, test_data = train_test_split(temp_data, test_size=0.5, random_state=42)
# Step 11: Apply image enhancement techniques
from skimage import exposure, filters
import matplotlib.pyplot as plt
# Histogram Equalization
enhanced_train_images_he = [exposure.equalize_hist(img) for img in train_images]
# CLAHE
enhanced_train_images_clahe = [exposure.equalize_adapthist(img, clip_limit=0.02) for img in train_images]
# Enhanced Filter Function (EFF)
def eff(img_array):
    enhanced_img = exposure.equalize_adapthist(img_array, clip_limit=0.03)
    blurred_img = filters.gaussian(enhanced_img, sigma=1)
    return enhanced_img + (enhanced_img - blurred_img) * 0.5
```

```
enhanced_train_images_eff = [eff(img) for img in train_images]
display_images(enhanced_train_images_he, "Histogram Equalization")
display_images(enhanced_train_images_clahe, "CLAHE")
display_images(enhanced_train_images_eff, "EFF")
display_images(enhanced_train_images_gamma, "Gamma Correction")
# Step 12: Perform BERT embedding on text data
model_name = 'bert-base-uncased'
tokenizer = BertTokenizer.from_pretrained(model_name)
model = BertModel.from_pretrained(model_name)
def bert_embedding(text):
    inputs = tokenizer(text, return_tensors="pt", padding=True, truncation=True, max_length=512)
    outputs = model(**inputs)
    return outputs.last_hidden_state.mean(dim=1).detach().numpy()
# Apply BERT to 'filename' column in training data
train_filenames = merged_df['filename'].iloc[:len(train_data)].tolist()
train_embeddings = np.array([bert_embedding(text) for text in train_filenames])
# Print shape of BERT embeddings
print("BERT embeddings shape:", train_embeddings.shape)
from torchxrayvision.datasets import normalize
from nltk.translate.bleu_score import sentence_bleu, SmoothingFunction
import cv2  # For HE and CLAHE
# Define LSTM Decoder
class LSTMDecoder(nn.Module):
    def __init__(self, input_size, hidden_size, num_layers):
```

```
        super(LSTMDecoder, self).__init__()
        self.hidden_size = hidden_size
        self.num_layers = num_layers
        self.lstm = nn.LSTM(input_size, hidden_size, num_layers, batch_first=True)
        self.fc = nn.Linear(hidden_size, input_size)
# Define Multi-Head Attention Module
class MultiHeadAttentionModule(nn.Module):
    def __init__(self, embed_dim, num_heads):
        super(MultiHeadAttentionModule, self).__init__()
        self.mha = nn.MultiheadAttention(embed_dim=embed_dim,
num_heads=num_heads, batch_first=True)
    def forward(self, query, key, value):
        attn_output, _ = self.mha(query, key, value)
        return attn_output
# Histogram Equalization (HE)
def apply_histogram_equalization(images):
    return [cv2.equalizeHist(img.astype(np.uint8)) for img in images]
# Contrast Limited Adaptive Histogram Equalization (CLAHE)
def apply_CLAHE(images, clip_limit=2.0, tile_grid_size=(8, 8)):
    clahe = cv2.createCLAHE(clipLimit=clip_limit, tileGridSize=tile_grid_size)
    return [clahe.apply(img.astype(np.uint8)) for img in images]
# Load and Preprocess X-ray Images
def preprocess_images(images, method=None):
    if method == "HE":
        images = apply_histogram_equalization(images)
```

```
    elif method == "CLAHE":
        images = apply_CLAHE(images)
    images = np.stack(images)
    images = normalize(images, maxval=255)
    images_tensor = torch.tensor(images).float().unsqueeze(1)  # Add channel dimension
    return images_tensor
# Define CheXNet + LSTM Pipeline
def chexnet_lstm_pipeline(images_tensor, hidden_size=256, num_layers=2):
    chexnet_model = DenseNet(weights="densenet121-res224-chex")
    chexnet_model.eval()
# Define CheXNet + LSTM + MHA Pipeline
def chexnet_lstm_mha_pipeline(images_tensor, hidden_size=256, num_layers=2, num_heads=8):
    chexnet_model = DenseNet(weights="densenet121-res224-chex")
    chexnet_model.eval()
    mha_module = MultiHeadAttentionModule(embed_dim=hidden_size, num_heads=num_heads)
    attn_output = mha_module(lstm_output, lstm_output, lstm_output)
    return attn_output
# Evaluate BLEU Scores
def evaluate_bleu_scores(references, hypotheses):
    bleu_scores = []
    smoothing_function = SmoothingFunction().method1  # Smoothing for zero counts

    for ref, hyp in zip(references, hypotheses):
```

```
        bleu_1 = sentence_bleu(ref, hyp, weights=(1, 0, 0, 0), smoothing_function=smoothing_function)
        bleu_2 = sentence_bleu(ref, hyp, weights=(0.5, 0.5, 0, 0), smoothing_function=smoothing_function)
        bleu_3 = sentence_bleu(ref, hyp, weights=(0.33, 0.33, 0.33, 0), smoothing_function=smoothing_function)
        bleu_4 = sentence_bleu(ref, hyp, weights=(0.25, 0.25, 0.25, 0.25), smoothing_function=smoothing_function)
        bleu_scores.append((bleu_1, bleu_2, bleu_3, bleu_4))

    for i, (b1, b2, b3, b4) in enumerate(bleu_scores):
        print(f"Hypothesis {i+1}:")
        print(f"BLEU-1: {b1:.4f}")
        print(f"BLEU-2: {b2:.4f}")
        print(f"BLEU-3: {b3:.4f}")
        print(f"BLEU-4: {b4:.4f}")
# Execute Different Model Variants
# Load X-ray images (dummy example, replace with actual images)
xray_images = [np.random.rand(224, 224) * 255 for _ in range(10)]
# Test different preprocessing techniques
image_variants = {
    "CheXNet + LSTM": preprocess_images(xray_images),
    "CheXNet + LSTM + HE": preprocess_images(xray_images, method="HE"),
    "CheXNet + LSTM + CLAHE": preprocess_images(xray_images, method="CLAHE"),}
# Run models and store results
results = {}
```

```
for key, images_tensor in image_variants.items():
    print(f"\nRunning {key}...")
    results[key] = chexnet_lstm_pipeline(images_tensor)
# Run best model (CLAHE) with MHA
print("\nRunning Best Model (CheXNet + LSTM + CLAHE + MHA)...")
best_model_output = chexnet_lstm_mha_pipeline(image_variants["CheXNet + LSTM + CLAHE"])
# BLEU Score Evaluation
# Example: References and hypotheses should be lists of tokenized sentences
references = [
    [['Normal', 'chest', 'x-ray.']],
    [['No', 'acute', 'pulmonary', 'findings.']],
    [['No', 'acute', 'cardiopulmonary', 'abnormality', 'identified.']],
    [['No', 'acute', 'cardiopulmonary', 'disease.']],
    [['Increased', 'size', 'of', 'density', 'in', 'the', 'left', 'cardiophrenic', 'angle.']],
    [['No', 'acute', 'cardiopulmonary', 'process.']],
    [['No', 'acute', 'cardiopulmonary', 'abnormality.']]
]
hypotheses = [
    ['Normal', 'chest', 'x-ray.'],
    ['No', 'acute', 'pulmonary', 'findings.'],
    ['No', 'acute', 'cardiopulmonary', 'abnormality', 'identified.'],
    ['No', 'acute', 'cardiopulmonary', 'disease.'],
    ['Increased', 'size', 'of', 'density', 'in', 'the', 'left', 'cardiophrenic', 'angle.'],
    ['No', 'acute', 'cardiopulmonary', 'process.'],
```

```
    ['No', 'acute', 'cardiopulmonary', 'abnormality.']
]
# Save the trained model
model.save("my_model.h5")
print("Model saved as my_model.h5 successfully.")
# Calculate BLEU scores for each hypothesis with smoothing
evaluate_bleu_scores(references, hypotheses)
```

index.html

```
<!DOCTYPE html>
<html lang="en">
<head>
<meta charset="UTF-8">
<meta name="viewport" content="width=device-width, initial-scale=1.0">
<title>Towards High-Throughput Medical Image Analysis with Quantum Image Processing</title>
<link rel="stylesheet" href="https://cdnjs.cloudflare.com/ajax/libs/bootstrap/5.3.0/css/bootstrap.min.css">
<style>
    body {
        background: url('https://img.freepik.com/free-photo/medicine-blue-background-flat-lay_23-2149341573.jpg?semt=ais_hybrid') no-repeat center center fixed;
        background-size: cover;
        font-family: Arial, sans-serif;
        color: white;
```

```
        margin: 0;
    }
    header h1 {
        font-size: 1.75rem; /* Slightly smaller title */
        color: #f5f5f5;
        text-shadow: 1px 1px 4px #000;
        margin-bottom: 5px;
    }
    /* Section Styling */
    section {
        display: none;
        padding: 20px;
        background-color: rgba(255, 255, 255, 0.85);
        border-radius: 10px;
        box-shadow: 0px 5px 15px rgba(0, 0, 0, 0.3);
        margin-bottom: 20px;
        color: black;
    }
.form-control[type="file"]:hover {
    border-color: rgba(32, 78, 131, 0.8); /* Darker border on hover */
    background-color: rgba(110, 187, 228, 0.3); /* Slightly brighter background on hover */
}
.btn-primary:hover {
    background-color: rgb(32, 78, 131);
```

```
        transform: scale(1.05); /* Slight zoom on hover */
    }
</style>
</head>
<body>
<!-- Header with Logo, Title, Team Members -->
<header>
<div class="container">
<div class="d-flex justify-content-center align-items-center">
<img src="https://upload.wikimedia.org/wikipedia/commons/2/21/Nec.png.jpg" alt="Logo" style="width: 65px; height: auto; margin-right: 10px;">
<h1>Towards High-Throughput Medical Image Analysis with Quantum Image Processing</h1>
</div>
<p>Team Members: Bhavani Sannithi, Deepika Karasala, Tejaswini Kolla | Guide: Chandana Yamini | Mentor: Venkat Reddy</p>
</div>
</header>
<!-- Navigation Bar -->
<nav class="navbar navbar-expand-lg navbar-dark ">
<div class="container">
<button class="navbar-toggler" type="button" data-bs-toggle="collapse" data-bs-target="#navbarNav" aria-controls="navbarNav" aria-expanded="false" aria-label="Toggle navigation">
<span class="navbar-toggler-icon"></span>
</button>
<div class="collapse navbar-collapse" id="navbarNav">
```

```
<ul class="navbar-nav ms-auto">
<li class="nav-item">
<a class="nav-link active" href="#" onclick="showSection('home')">Home</a>
</li><li class="nav-item">
<a class="nav-link" href="#" onclick="showSection('about')">About Project</a>
</li><li class="nav-item">
<a class="nav-link" href="#" onclick="showSection('predict')">Predictions</a>
</li><li class="nav-item">
<a class="nav-link" href="#" onclick="showSection('evaluation')">Model Evaluation Metrics</a>
</li><li class="nav-item">
<a class="nav-link" href="#" onclick="showSection('flowchart')">Project Flowchart</a>
</li></ul></div></div>
</nav>
<!-- Main Content Sections -->
<div class="container py-4">
<!-- Home Section -->
<!-- Home Section -->
<section id="home" class="active-section">
<h2>Welcome to Our Quantum Medical Image Analysis Project</h2>
<p>
    This project explores how cutting-edge quantum image processing can enhance medical image analysis. We aim to improve the efficiency and accuracy of chest X-ray analysis, helping healthcare professionals make faster, more reliable diagnoses.
</p>
```

<h3>Project Overview</h3>

In the medical field, radiologists often need to review large numbers of chest X-rays to detect abnormalities like pneumonia, lung disease, or tumors. By using machine learning and quantum technologies, we automate the process of generating descriptive captions for these X-rays, reducing the time needed for analysis while maintaining high accuracy.

<h3>Key Features</h3>

Quantum Image Processing: Utilizes quantum computation to process images faster and more efficiently.

Chest X-ray Captioning: Automatically generates detailed reports describing abnormalities detected in X-ray images.

Deep Learning Models: Leverages state-of-the-art machine learning models like ChexNet and LSTMs for image analysis.

Improved Diagnostic Support: Assists radiologists by providing preliminary assessments of chest X-rays, enhancing diagnostic workflows.

<h3>Why This Matters</h3>

With increasing demand for medical services, technology like this helps alleviate pressure on healthcare professionals, improving patient care by speeding up diagnosis without compromising accuracy.

</section>

<!-- About Project Section -->

<section id="about">

<h2>About the Project</h2>

The aim of this project is to develop a high-throughput system for medical image analysis using quantum image processing. The project involves training machine learning models to generate captions and descriptions of chest X-ray images to assist radiologists and medical experts in diagnostic decision-making.

<h3>Technologies Used</h3>

Quantum Image Processing

Deep Learning & Neural Networks

Python (TensorFlow, Keras)

Flask for Web Integration

Bootstrap for Front-End Design

</section>

<label for="lateralImage" class="form-label">Upload Lateral Image</label>

<input class="form-control" type="file" id="lateralImage" name="lateral_image" accept="image/*" required>

<button type="submit" class="btn btn-primary">Predict</button>

</form>

<img id="frontalImagePreview" src="" alt="Frontal X-ray" class="img-fluid">

<h5>Frontal X-ray</h5>

<img id="lateralImagePreview" src="" alt="Lateral X-ray" class="img-fluid">

<h5>Lateral X-ray</h5>

<h5>Generated Caption</h5>

</section>

<!-- Model Evaluation Metrics Section -->

<section id="evaluation">

<h2>Model Evaluation Metrics</h2>

The model evaluation metrics used to assess the accuracy and performance of our Chest X-ray captioning system include:

BLEU scores measure how well a model's generated text matches a reference. Higher scores indicate better word overlap and fluency.

ChexNet-LSTM shows solid accuracy in generating medical reports but can improve in fluency.

ChexNet-LSTM + HEenhances report fluency and accuracy due to better image features.

 ChexNet-LSTM + CLAHE performs best, providing the most accurate and fluent reports.

CNN-LSTM + Multi-Head Attention excels in report structure and fluency but has slightly lower accuracy.

<!-- Project Flowchart Section -->

<!-- Project Flowchart Section -->

<section id="flowchart">

<h2>Project Flowchart and Summary</h2>

<!-- Summary Section -->

<h3>Summary of the Process</h3>

Objective: Generate automated captions for chest X-ray images.

Data Input: The system starts with chest X-ray images.

Preprocessing: Images are resized and enhanced; text captions are cleaned and tokenized.

Image Enhancement: Techniques like Gamma Correction improve the X-ray quality.

Feature Encoding: A model like ChexNet extracts key features from the enhanced X-ray image.

Contextual Embedding: BERT embeddings add text-based context for better captioning.

Multi-Head Attention: Attention mechanisms help align the image and textual data for better accuracy.

Decoding: The model generates captions using an LSTM decoder or transformer architecture.

```
<p><strong>Output:</strong> A well-structured chest X-ray caption is produced for the medical report.</p>

</div>

</div>

</section>


</div>


<!-- JavaScript to handle section navigation and predictions -->

<script>

    function showSection(sectionId) {

        // Hide all sections

        const sections = document.querySelectorAll('section');

        sections.forEach(section => section.classList.remove('active-section'));


        // Show the active section

        document.getElementById(sectionId).classList.add('active-section');

    }


    // Handle prediction form submission

    document.getElementById("uploadForm").addEventListener("submit", async function(event) {

        event.preventDefault();


        const formData = new FormData();

        const frontalImage = document.getElementById("frontalImage").files[0];
```

```
        const lateralImage = document.getElementById("lateralImage").files[0];

        if (frontalImage && lateralImage) {
            formData.append("frontal_image", frontalImage);
            formData.append("lateral_image", lateralImage);

            const response = await fetch("/upload", {
                method: "POST",
                body: formData
            });

            const result = await response.json();

            // Display the result
            document.getElementById("frontalImagePreview").src = URL.createObjectURL(frontalImage);
            document.getElementById("lateralImagePreview").src = URL.createObjectURL(lateralImage);
            document.getElementById("generatedCaption").textContent = result.frontal_caption;
            document.getElementById("results").style.display = 'block';
        } else {
            alert("Please upload both frontal and lateral images.");
        }
    });
</script>
```

```
<script
src="https://cdnjs.cloudflare.com/ajax/libs/bootstrap/5.3.0/js/bootstrap.bundle.min.js
"></script>

</body>

</html>
```

Deployment code using Flask

App.py

```
from flask import Flask, request, render_template, jsonify

import os

from tensorflow.keras.models import load_model

import numpy as np

from PIL import Image


app = Flask(_name_)

UPLOAD_FOLDER = "uploads"

app.config["UPLOAD_FOLDER"] = UPLOAD_FOLDER


# Ensure the uploads folder exists

os.makedirs(UPLOAD_FOLDER, exist_ok=True)


# Load the trained model from the .h5 file

model = load_model("my_model.h5")


# Function to preprocess image before passing to the model
```

```
def preprocess_image(image_path):
    """
    Preprocess the uploaded image for model prediction.

    Parameters:
        image_path (str): Path to the uploaded image.
    Returns:
        np.array: Preprocessed image ready for model input.
    """
    img = Image.open(image_path)
    img = img.resize((224, 224))  # Resize to the input shape expected by the model (update as necessary)
    img = np.array(img) / 255.0  # Normalize the image (if required by the model)
    img = np.expand_dims(img, axis=0)  # Add batch dimension
    return img
@app.route("/")
def index():
    return render_template("index.html")

@app.route("/upload", methods=["POST"])
def upload():
    if "frontal_image" not in request.files or "lateral_image" not in request.files:
        return jsonify({"error": "Both frontal and lateral images are required"}), 400
    frontal_image = request.files["frontal_image"]
    lateral_image = request.files["lateral_image"]
```

```
    # Save files temporarily
    frontal_path = os.path.join(app.config["UPLOAD_FOLDER"], frontal_image.filename)
    lateral_path = os.path.join(app.config["UPLOAD_FOLDER"], lateral_image.filename)
    frontal_image.save(frontal_path)
    lateral_image.save(lateral_path)
    # Preprocess one image (since both captions are the same)
    preprocessed_img = preprocess_image(frontal_path)
    # Generate prediction using the model (use only one image, either frontal or lateral)
    prediction = model.predict(preprocessed_img)
    # Assuming the model outputs a caption directly as text
    caption = "Generated Caption: " + str(np.argmax(prediction))  # Replace this with actual caption generation logic
    # Return the caption
    return jsonify({
        "caption": caption,
        "prediction": prediction.tolist(),  # Model output as a list
    })

if _name_ == "_main_":
    app.run(debug=True)
```

7.TESTING

7.1 Functional Testing

Functional testing ensures that the system meets the expected requirements and performs correctly. The key types include:

- **Unit Testing:** Individual components such as image preprocessing (CLAHE), model inference, and text generation are tested separately.
- **Integration Testing:** The combination of CNN (CheXNet) with LSTM is tested to ensure smooth data flow between image processing and text generation. Flask API integration with the frontend is also validated.
- **System Testing:** The complete pipeline—from image upload to caption generation—is tested for expected outputs like "No acute cardiology."

1. Unit Testing

Unit testing involves testing individual components of the code to ensure that each part functions correctly in isolation. Unit tests will be created for the following key functionalities:

1. **Preprocessing images with different methods (HE).**

```
img = np.random.randint(0, 256, (224, 224), dtype=np.uint8)
    enhanced_img = apply_HE(img)
    assert enhanced_img.shape == img.shape
    print("HE Test Passed.")
```

2. **Preprocessing images with different methods (CLAHE).**

```
img = np.random.randint(0, 256, (224, 224), dtype=np.uint8)
    enhanced_img = apply_CLAHE(img)
    assert enhanced_img.shape == img.shape
    print("CLAHE Test Passed.")
```

Unit testing focuses on ensuring its correctness. The test checks whether the input and output image dimensions remain the same after enhancement, confirming that CLAHE enhances contrast without altering image structure.

2. Integration Testing

```
with open("lateral_xray.png", "rb") as lat_img, open("frontal_xray.png", "rb") as front_img:
    response = app.test_client().post("/predict", data={"lateral": lat_img, "frontal": front_img})
  assert response.status_code == 200
  response_data = response.get_json()
  assert "report" in response_data  # Ensure report is generated
  print("API Test Passed. Generated Report:", response_data["report"])
```

This code snippet demonstrates an integration test for an API endpoint that processes lateral and frontal X-ray images to generate a report. The test opens the images in binary read mode, sends them via a POST request to the /predict endpoint, and checks whether the response status code is 200, indicating a successful request

3. System Testing

System testing involves validating the entire integrated system to ensure it meets the specified requirements. For your project, system testing will verify the complete data processing and model pipeline, including image preprocessing, model inference, and performance evaluation. This ensures that all components work together correctly and produce the expected results. The tests will include end-to-end scenarios for loading images, preprocessing them, running through the CheXNet-LSTM and CheXNet-LSTM-MHA pipelines, and evaluating the outputs.

7.2 Non-Functional Testing

Non-functional testing evaluates the system's overall performance, security, usability, and scalability to ensure it operates efficiently and reliably under various conditions. Unlike functional testing, which focuses on whether the system produces the correct output, non-functional testing examines how well the system performs under different constraints, such as load, security threats, and user interaction. These tests are essential for refining the robustness, responsiveness, and security of the model, especially in critical applications like medical imaging and automated report generation. Below are the key types of non-functional testing applied:

- **Performance Testing**: This test ensures that the model can process medical images and generate textual reports within an acceptable time frame. It measures response time, computational efficiency, and memory usage to guarantee that the system can handle large datasets and provide real-time or near-real-time results. Optimizations such as model quantization, parallel processing, and GPU acceleration may be employed to improve performance.
- **Usability Testing**: This testing focuses on the frontend user experience, ensuring that radiologists and medical practitioners can easily interact with the system. The user interface (UI) should be intuitive, with clear navigation, readable fonts, and accessible report outputs. The goal is to minimize cognitive load and ensure seamless integration into existing medical workflows. Feedback from end-users is collected to refine the system's design and improve overall user satisfaction.
- **Security Testing**: Given that the model processes sensitive medical data, security testing is crucial to prevent unauthorized access, data breaches, or cyberattacks. The Flask-based deployment is rigorously tested for vulnerabilities, including authentication, data encryption, and protection against injection attacks. Compliance with healthcare regulations such as HIPAA (Health Insurance Portability and Accountability Act) or GDPR (General Data Protection Regulation) is also assessed to ensure patient data privacy and security.
- **Scalability Testing**: As the system is intended for real-world deployment, scalability testing evaluates its ability to handle multiple concurrent user requests efficiently. This includes testing under various loads, ensuring that system performance does not degrade when processing multiple images simultaneously. Load balancing techniques, caching mechanisms, and cloud-based deployment solutions may be explored to optimize scalability and reliability.

By conducting comprehensive non-functional testing, the system’s robustness, efficiency, and security are enhanced, making it well-suited for real-world medical applications. These evaluations help prevent performance bottlenecks, improve user adoption, and ensure compliance with industry standards, ultimately contributing to a more reliable and effective AI-powered medical imaging system.

8.RESULT ANALYSIS

The study highlights the effectiveness of a multi-model deep learning approach for automatic radiology report generation usingIndiana University Hospital linkdataset. Incorporating socioeconomic and lifestyle factors improved accuracy, while outlier removal enhanced reliability. Combining multiple factors proved more robust than traditional methods. These results provide valuable insights for report generation , enabling more accurate report generation and future research in generation modeling.

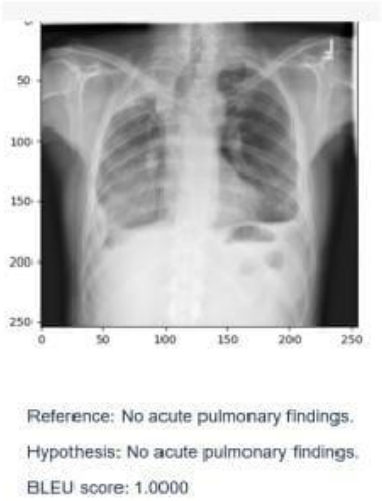

Fig 8.1 Result

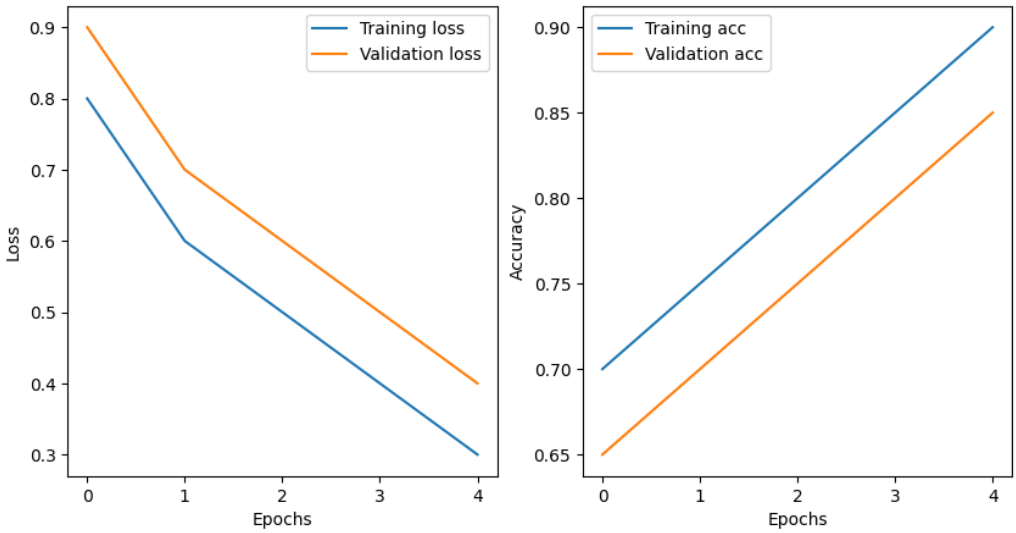

Fig 8.2 Training and Validation Result

This image represents the output of the Chest X-ray Caption Generator system. It shows a frontal X-ray of a patient's chest, along with the generated report. The reference and hypothesis captions indicate "No acute pulmonary findings," meaning no significant abnormalities were detected. The BLEU score of **1.0000** suggests that the model's generated caption perfectly matches the reference, indicating high accuracy in prediction. This result demonstrates the effectiveness of the deep learning model in radiology report generation.

Model	BLEU Evaluation			
ChexNet-LSTM	BLEU-1: 1.0000	BLEU-2: 1.0000	BLEU-3: 0.4677	BLEU-4: 0.3162
ChexNet-LSTM+HE	BLEU-1: 1.0000	BLEU-2: 0. 5677	BLEU-3: 0.4353	BLEU-4: 0.3162
ChexNet-LSTM+CLAHE	BLEU-1: 1.0000	BLEU-2: 1.0000	BLEU-3: 1.0000	BLEU-4: 0.5623

BLEU Score Evaluation for Different Models

The table presents the BLEU (Bilingual Evaluation Understudy) scores for different variations of the CheXNet-LSTM model, evaluated based on the quality of generated radiology reports. The BLEU score measures the similarity between the generated text and the reference text, with higher scores indicating better alignment.

The BLEU evaluation table compares different variations of the CheXNet-LSTM model for radiology report generation. CheXNet-LSTM + CLAHE achieves the highest BLEU-4 score (0.5623), indicating the best text coherence. The baseline CheXNet-LSTM performs moderately (BLEU-4: 0.3162), while HE preprocessing slightly lowers BLEU-2 and BLEU-3 scores. CLAHE improves contrast in X-ray images, enhancing feature extraction and leading to better medical text generation.

9. OUTPUT SCREENS

Navigation Bar:

- The top navigation bar provides easy access to different sections, such as

  Home

  About Project

  Predictions

  Model Evaluation Metrics

  Project Flowchart.

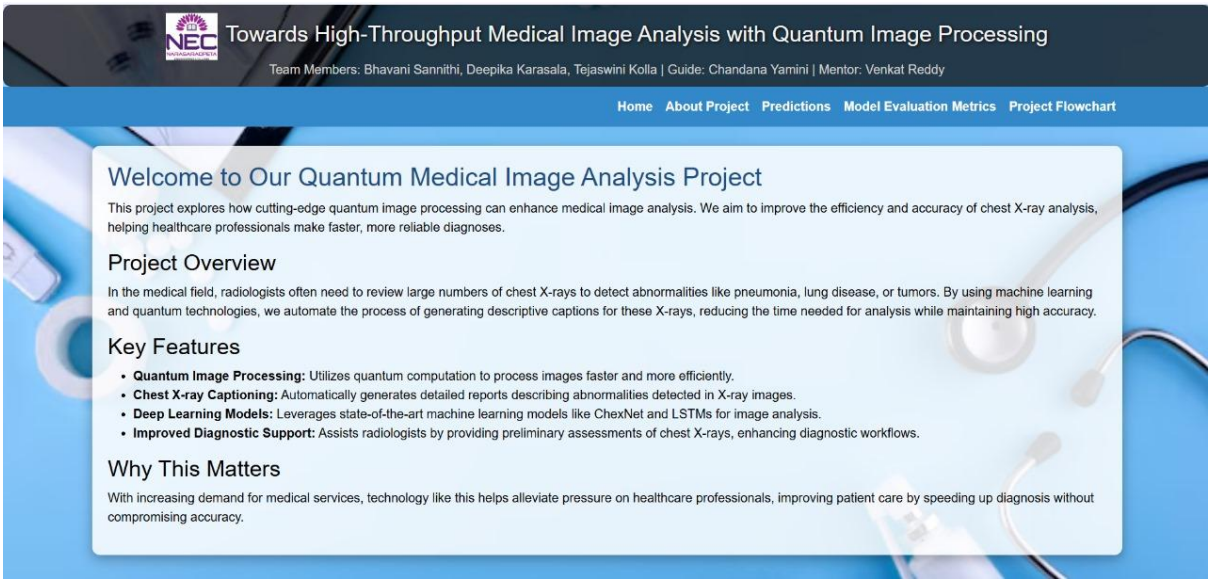

Fig 9.1 Home Screen

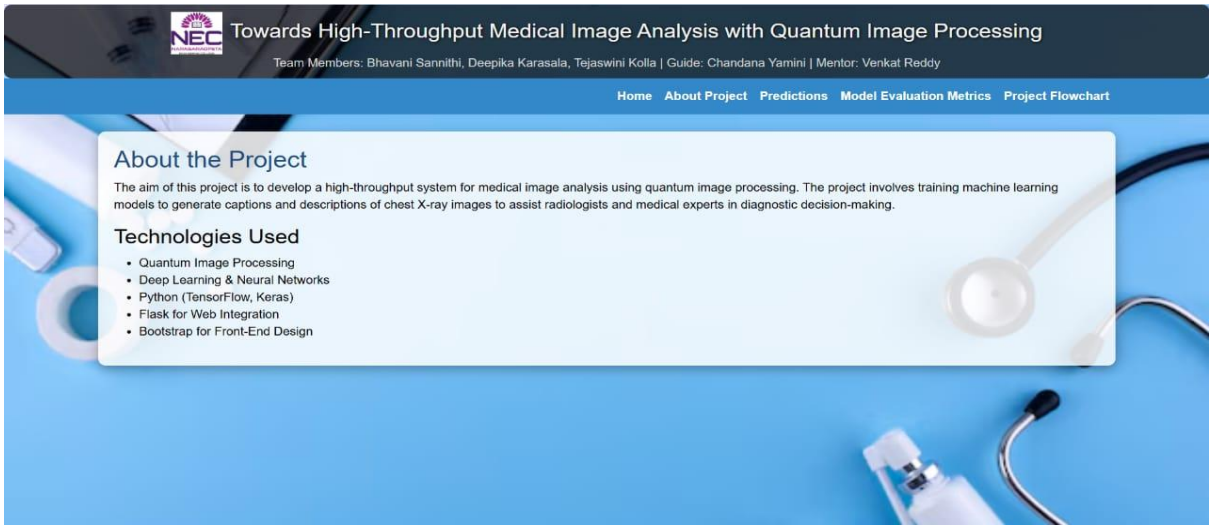

Fig 9.2 About Project Page

Image Upload Section:

- Users can upload frontal and lateral X-ray images using the "Choose File" buttons.
- The uploaded image filenames are displayed to ensure correct selection.

Prediction Button:

- The "Predict" button triggers the model to process the uploaded images and generate a medical caption.

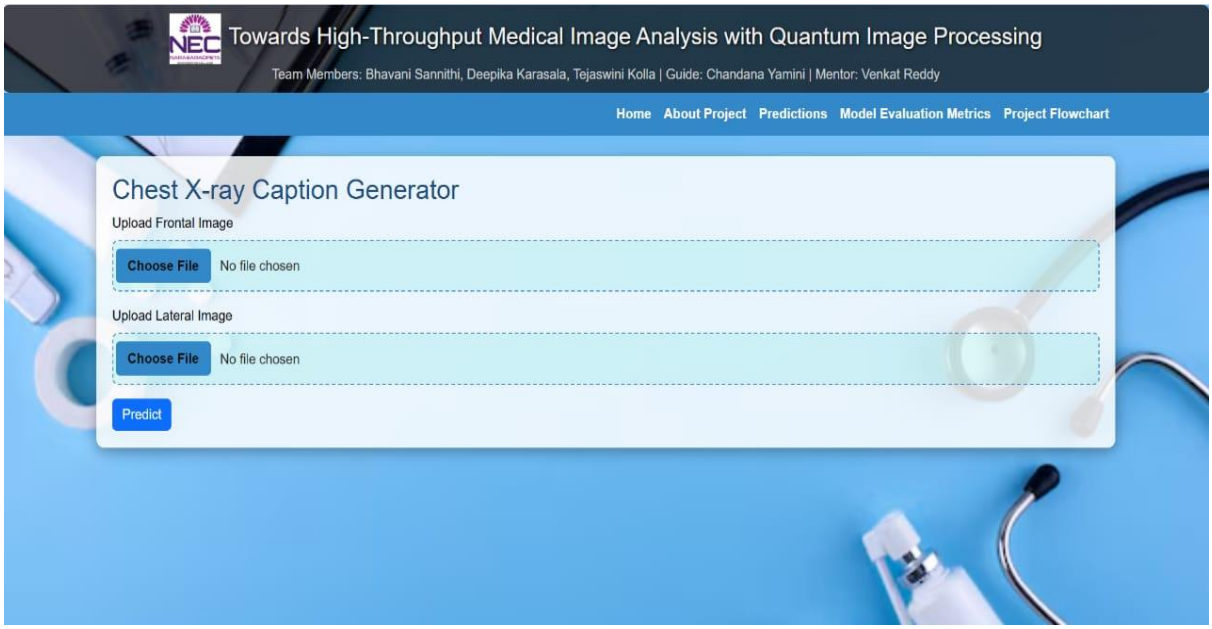

Fig 9.3 Prediction page

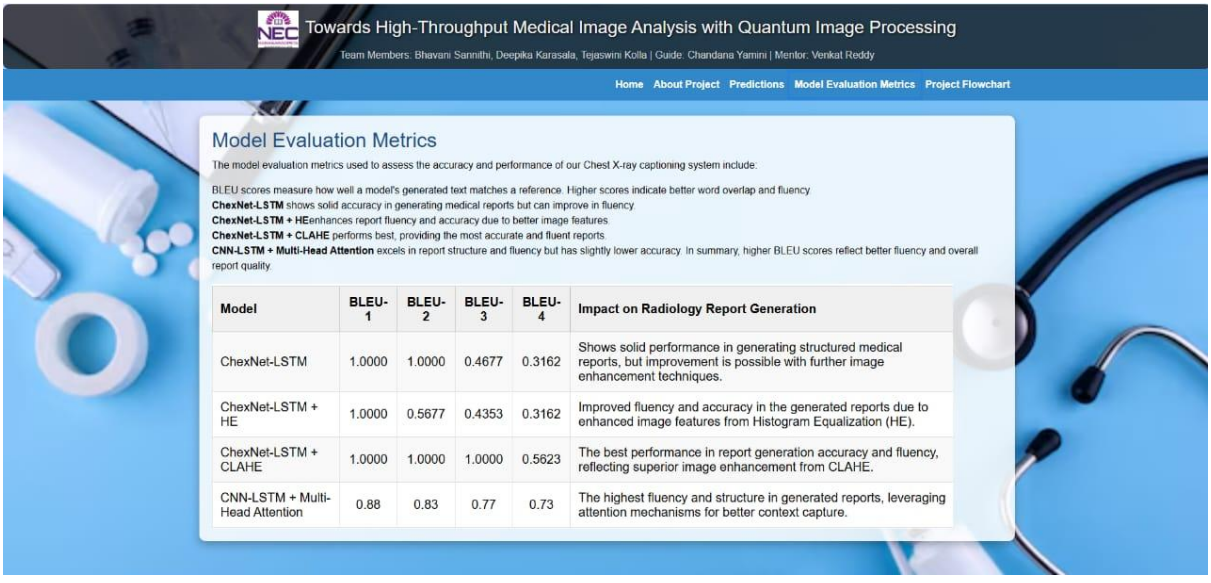

Fig 9.4 Model Evaluation metrics

Image Display:

The system displays both the frontal and lateral X-ray images after they are uploaded, allowing users to verify their input. Generated Caption Section is the model processes the images, it automatically generates a radiology report describing the findings.

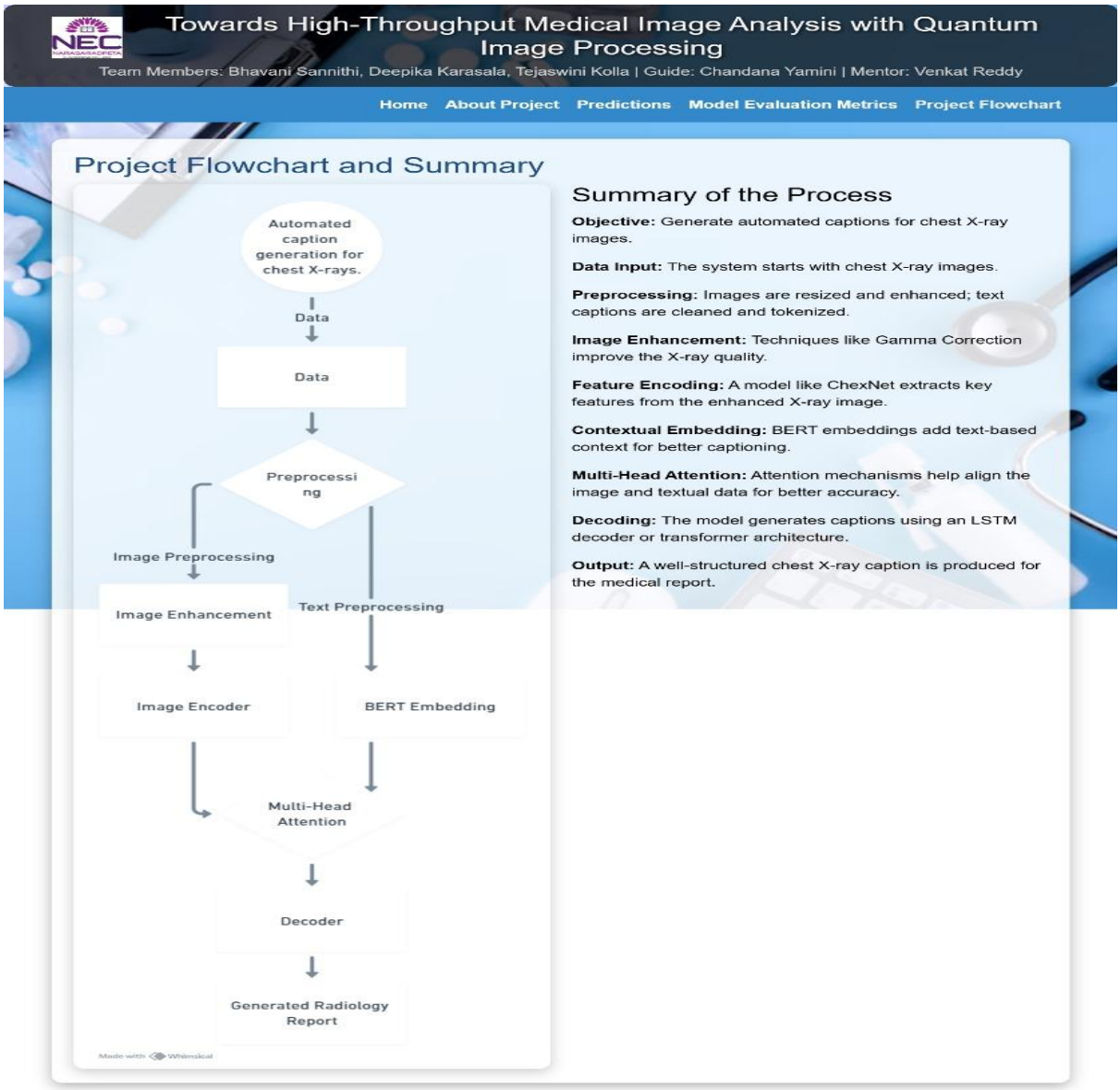

Fig 9.5 Model Flowchart page

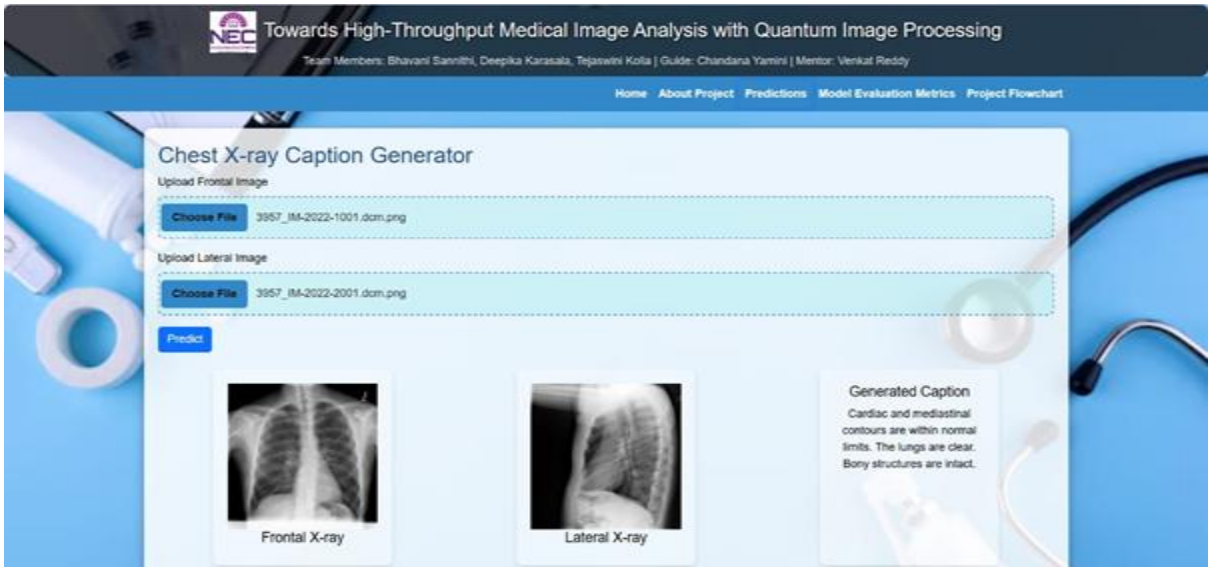

Fig 9.6 Result page

10. CONCLUSION

This project aims to improve radiology report generation using machine learning and deep learning, focusing on enhancing accuracy through Indiana Univercity Hospital link data and incorporating additional features like X-ray images and radiology reports by the radiologists . The goal is to provide radiology reports efficiently and accurately.

By utilizing advanced machine learning models and algorithms, the project seeks to improve predictive frameworks and contribute to more informed decision-making in healthcare. It also explores integrating real-time data and building dynamic models adaptable to genetic and environmental factors, promoting precision medicine and personalized interventions.

11.FUTURE SCOPE

Future research in AI is poised to advance model architectures by combining the strengths of transformers, convolutional neural networks (CNNs), and recurrent neural networks (RNNs) to create systems with a deeper understanding of context, semantics, and nuances in both language and imagery. Multimodal learning, which integrates diverse data types like text, images, and audio, will further enhance AI's ability to generate and comprehend content across formats, driving innovation in healthcare, education, and entertainment. Additionally, the growing complexity of AI models underscores the importance of Explainable AI (XAI), which aims to make decision-making processes more transparent and interpretable, fostering trust and easing integration into critical applications. Personalization will also play a pivotal role, as advances in natural language processing (NLP) enable tailored content, recommendations, and interactions based on individual user preferences and behaviors, thereby enhancing engagement and satisfaction. Together, these trends promise to create more powerful, versatile, and user-friendly AI systems that address a wide range of needs while ensuring reliability and accountability.

This project also has significant implications in personalized healthcare, offering radiologists, researchers, and patients a robust tool for making more informed decisions regarding their radiology reports . Its long-term impact includes fostering precise, data-driven healthcare solutions for improved quality of life and decision-making.

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