Welcome

NARASARAOPETA ENGINEERING COLLEGE (AUTONOMOUS)

Department of Computer Science and Engineering

Towards High-Throughput Medical Image Analysis with Quantum Image Processing

PRESENTED BY

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OUTLINE

ABSTRACT

- **Automated Report Generation**: An automated system is designed to generate radiology reports.

- **Image and Text Processing**: Chest X-ray images are enhanced using methods like Histogram Equalization and CLAHE, while text is cleaned and processed with BERT embeddings for contextual accuracy.

- **Diagnosis**: The system uses Multi-Head Attention to produce clear and relevant reports, helping radiologists diagnose faster.

INTRODUCTION

- **Overview**: The project creates an automated system for generating chest X-ray reports.
- **Motivation**: Increasing radiologists' workload requires tools to produce timely and accurate reports efficiently.
- **Importance and Relevance**: Enhances diagnostic accuracy with improved image quality and structured report generation.

LITERATURE SURVEY

s.no	Year of publishing	Title	Dataset	Modals	Methodology	Key findings
1	2024	Automatic Radiology Report Generator Using Transformer With Contrast-Based Image Enhancement	Indiana University Hospital Link collection	Densent121 ChexNet ,BERT, Multi-Head Attention (MHA)	Improving X-ray images and text, extracting features, aligning with Multi-Head Attention, evaluating performance.	Image Enhancement Impact,Importance of Contrast Enhancement,Model Performance, MHA
2	2022	Intraoperative Glioma Grading Using Neural Architecture Search and Multi-Modal Imaging	The dataset used in the PDF file "Intraoperative Glioma Grading Using Neural Architecture Search and Multi-Modal Imaging" consisted of multi-modal imaging data . Histopathologic results served as the gold standard for grading the gliomasduring surgery [T2].	White Light (WL) Near-Infrared I (NIR-I) Near-Infrared II (NIR-II)	Neural Architecture Search for glioma grading using multi-modal imaging.	1. DLS-DARTS outperformed manually designed CNNs for glioma grading .,2. Multi-modal imaging provided richer information for improved model performance 3. DLS-DARTS enabled real-time sample-level glioma grading during surgery

LITERATURE SURVEY

s.no	Year of publishing	Title	Dataset	Modals	Methodology	Key findings
3	2017	Anatomically Constrained Neural Networks (ACNNs): Application to Cardiac Image Enhancement and Segmentation	UK Digital Heart Project Dataset,CETUS'14 Challenge Dataset, ACDC MICCAI'17 Challenge Dataset	Anatomically Constrained Neural Networks (ACNNs), Convolutional Neural Networks (CNNs), Fully Convolutional Network (FCN), T-L architecture.	Incorporating anatomical constraints into neural networks for cardiac image analysis.	Improved Segmentation Robustness,Implicit Statistical Parametrization,Enhanced Image Super-Resolution,High-Resolution Analysis
4	2020	A New Trend of Quantum Image Representations	The focus is primarily on discussing different quantum image representations, processing algorithms, challenges, and future research directions in the field of quantum image processing	FRQI, NEQR, IFRQI, QBIR, OQIM, QIIR, and DQRCI.	quantum image representations, processing algorithms, challenges, and future directions in quantum image processing.	Different quantum image representations have specific advantages and limitations for image storage and processing. Quantum image representations have expanded beyond the initial three classic models.

LITERATURE SURVEY

s.no	Year of publishing	Title	Dataset	Modals	Methodology	Key findings
5	2020	AI in Medical Imaging Informatics: Current Challenges and Future Directions	However, it discusses the importance of interoperable and explainable research in the context of healthcare innovation	medical imaging informatics, including challenges in data management, advancements in medical imaging acquisition technologies,	Focusing on data management, data analytics, deep learning methods, and the potential impact on precision medicine	Hardware breakthroughs in medical image acquisition have facilitated high-throughput and high-resolution images across imaging modalities, leading to unprecedented performance and lower induced radiation
6	2022	Parallel Discrete Convolutions on Adaptive Particle Representations of Images	Poisson-Gaussian denoising dataset with real fluorescence microscopy images	Richardson-Lucy deconvolution Multiscale methods for convolution neural networks OpenMP for shared-memory programming	Convolution on Adaptive Particle Representations on parallel architectures.	Efficient image processing, reduced memory consumption, improved runtime
7	2021	Active Contour Image Segmentation Method for Training Talents of Computer Graphics and Image Processing Technology	The active contour image segmentation method for training talents in computer graphics and image processing technology	CV model, LBF model, LGIF model, and K-LGIF model.	Active contour image segmentation based on graphics and image processing technology.	Combination of clustering and kernel function replacement enhances segmentation effectiveness.

LITERATURE SURVEY

s.no	Year of publishing	Title	Dataset	Modals	Methodology	Key findings
8	2014	Edge-Guided Dual-Modality Image Reconstruction	NCAT phantom with modifications	Computed Tomography (CT) Magnetic Resonance Imaging (MRI)	Edge-guided dual-modality image reconstruction with priori information	1. Improved image reconstruction with under-sampled data.,2. Effective compensation of missing information between modalities.
9	2023	Exploring Simple and Transferable Recognition-Aware Image Processing	ImageNet benchmark	ResNet-18 ResNet-50 ResNet-101 DenseNet-121 VGG-16	Simple methods for enhancing machine recognition of image processing outputs.	Decision boundary analysis of recognition models. Improved machine recognizability transferable to different contexts.
10	2022	Comprehensive Comparison of Image Quality Aspects Between Conventional and Plane-Wave Imaging Methods on a Commercial Scanner	The dataset used in this PDF is channel data recorded by 14L5 and 10L4 transducers on a prototype Sequoia US system.	14L5 10L4	Comparison of CPWCI and CFI on a commercial scanner for ABVSs.	Contrast sensitivity Resolution Contrast-to-noise ratio

RESEARCH GAPS

- There is a need for more efficient ways to **synchronize medical images** with corresponding textual descriptions, ensuring high-quality alignment between inputs and outputs.

- Current models may struggle with **accurate medical term generation**, especially for uncommon findings or nuanced conditions.

- Models trained on specific datasets may not **generalize well** to diverse medical environments or imaging devices.

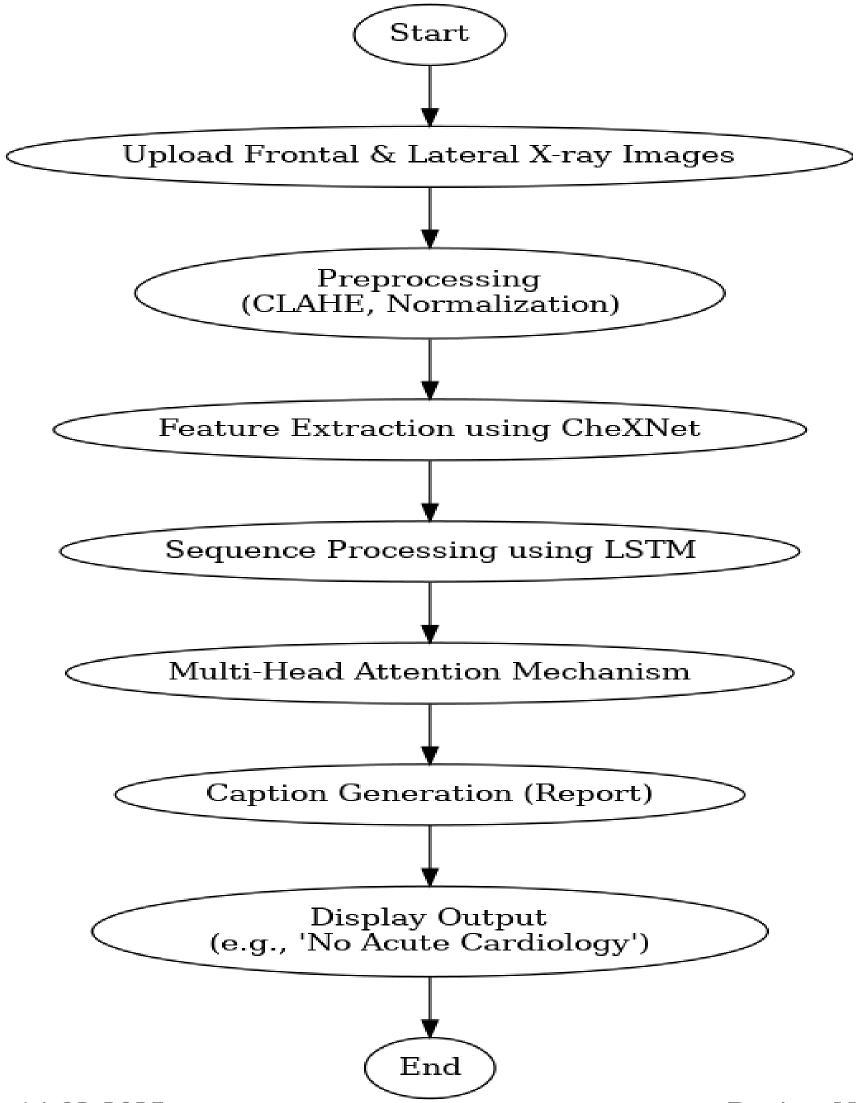
PROBLEM STATEMENT

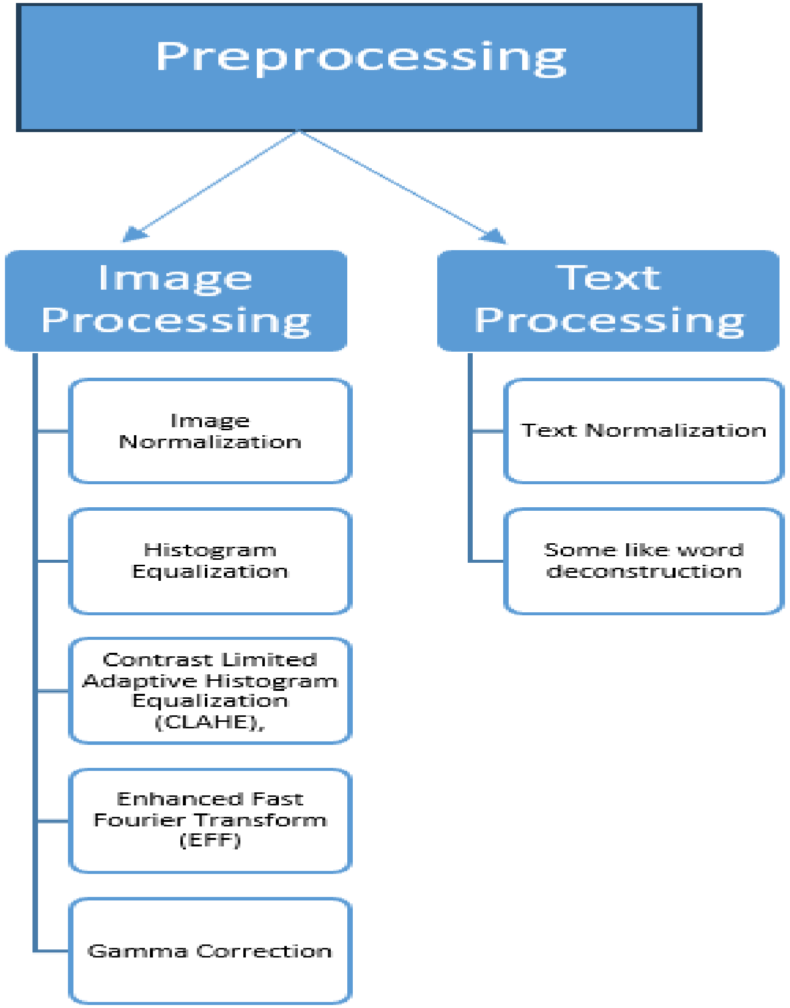
Chest X-ray interpretation is complex, requiring radiology expertise and time, often leading to inconsistencies and delays. This project develops a deep learning model (CheXNet-LSTM with CLAHE+MHA) to enhance contrast, efficiently process medical features, and generate accurate diagnostic reports, improving efficiency, accuracy, and accessibility in medical imaging.

OBJECTIVES

Develop a deep learning-based automated chest X-ray report system using CheXNet-LSTM with Multi-Head Attention. Enhance contrast with CLAHE for better disease detection and ensure accurate caption generation. Improve diagnostic efficiency by reducing manual effort and interpretation time while providing reliable reports for medical professionals.

BLOCK DIAGRAM OR FLOW DIAGRAM





METHODOLOGY

Data Acquisition & Preprocessing

- **Input**: Two chest X-ray images (Frontal & Lateral).
- **Preprocessing**:
  - Apply CLAHE for contrast enhancement.
  - Resize and normalize images.
  - Convert to grayscale (if needed).

METHODOLOGY

Both image and text data underwent preprocessing to ensure proper alignment for training.

Image Preprocessing:

Resizing: Standardized all images to **224x224 pixels** for consistency.

Normalization: Scaled pixel values to **[0,1]** to improve model performance and convergence.

METHODOLOGY

Augmentation & Filtering: Applied to enhance diversity and maintain alignment with captions.

Text Preprocessing:

Cleaning, tokenization, and padding were performed for structured input.

These steps ensured a well-prepared dataset for efficient training.

METHODOLOGY

Model Development & Evaluation

- **Feature Extraction**:
  - CheXNet (pretrained CNN) extracts image features.
- **Caption Generation**:
  - LSTM processes sequential features.
  - Multi-Head Attention improves context understanding.
- **Evaluation**: BLEU scores are used to measure caption accuracy.

IMPLEMENTATION

Software Specifications

•**Programming Language**: Python

•**Frameworks**: TensorFlow, Keras, OpenCV, Flask

•**Libraries**: NumPy, Pandas, Matplotlib

Hardware Specifications

•**Processor**: Intel i5/i7 or equivalent

•**RAM**: 8GB or more

IMPLEMENTATION

```
# Load Pretrained Model (CheXNet)
model =
tf.keras.applications.DenseNet121(weights='imagenet',
include_top=False)

# Apply CLAHE
def apply_CLAHE(img):
    clahe = cv2.createCLAHE(clipLimit=2.0,
tileGridSize=(8,8))
    return clahe.apply(img)
```

IMPLEMENTATION

```
# Feature Extraction
def extract_features(image):
    image = preprocess(image)  # Resize, normalize
    features = model.predict(image)
    return features

# LSTM Model for Captioning
def build_captioning_model():
    input_img = Input(shape=(1024,))
    lstm = LSTM(256, return_sequences=True)(input_img)
    attention = MultiHeadAttention(num_heads=8, key_dim=256)(lstm, lstm)
    output = Dense(vocab_size, activation='softmax')(attention)
    return Model(inputs=input_img, outputs=output)
```

IMPLEMENTATION

```
# Predict Caption
def generate_caption(img1, img2):
    features1 = extract_features(img1)
    features2 = extract_features(img2)
    combined_features = np.concatenate((features1, features2), axis=1)
    caption = model.predict(combined_features)
    return caption
```

RESULT & ANALYSIS

Reference: No acute pulmonary findings.
Hypothesis: No acute pulmonary findings.
BLEU score: 1.0000

Fig 8.1:Result

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

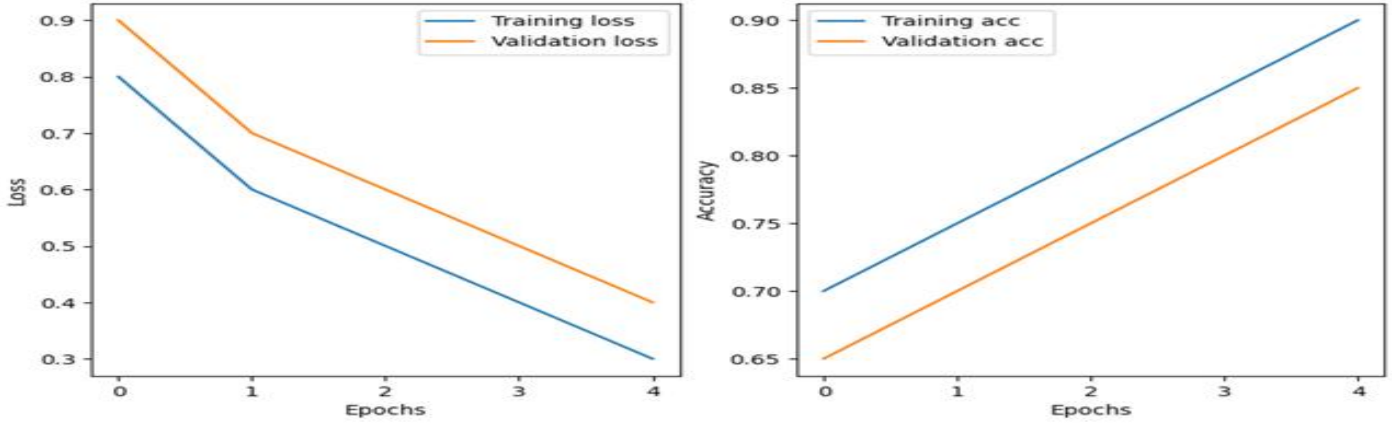
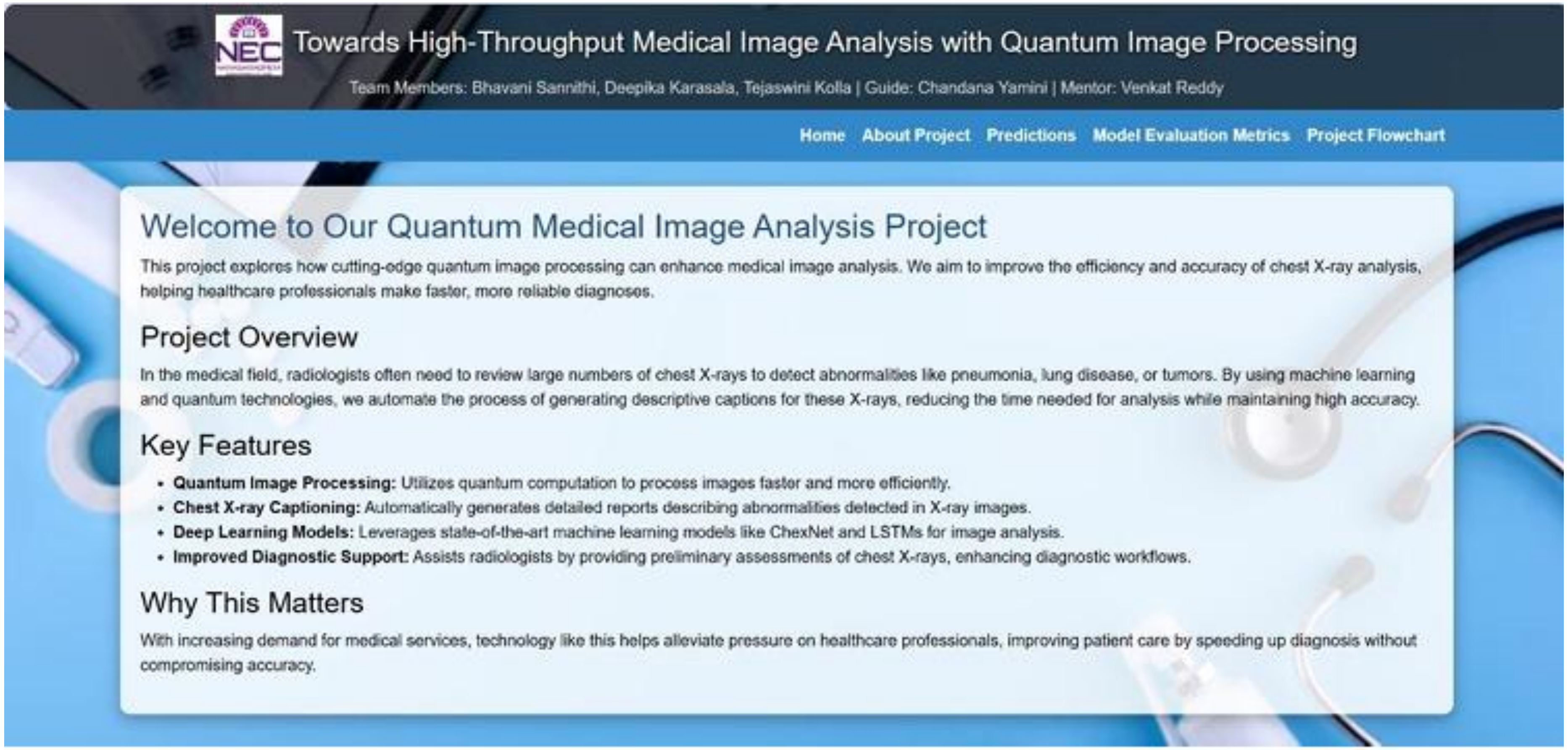


Fig 8.2 Training and Validation Result

OUTPUT SCREENS



OUTPUT SCREENS

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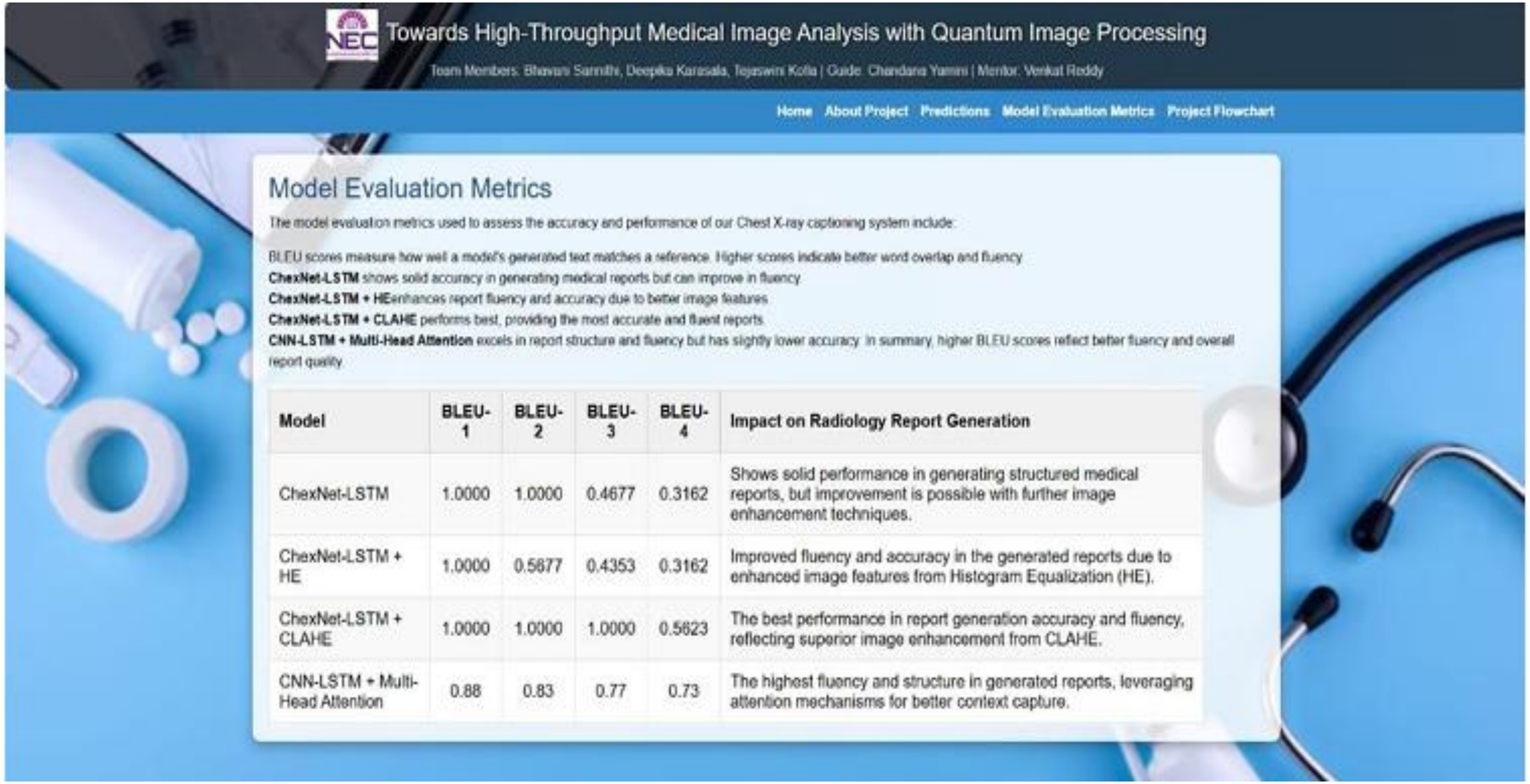

Towards High-Throughput Medical Image Analysis with Quantum Image Processing

Team Members: Bhavani Sannithi, Deepika Karasala, Tejaswini Kolla | Guide: Chandana Yamini | Mentor: Venkat Reddy

Home About Project Predictions Model Evaluation Metrics Project Flowchart

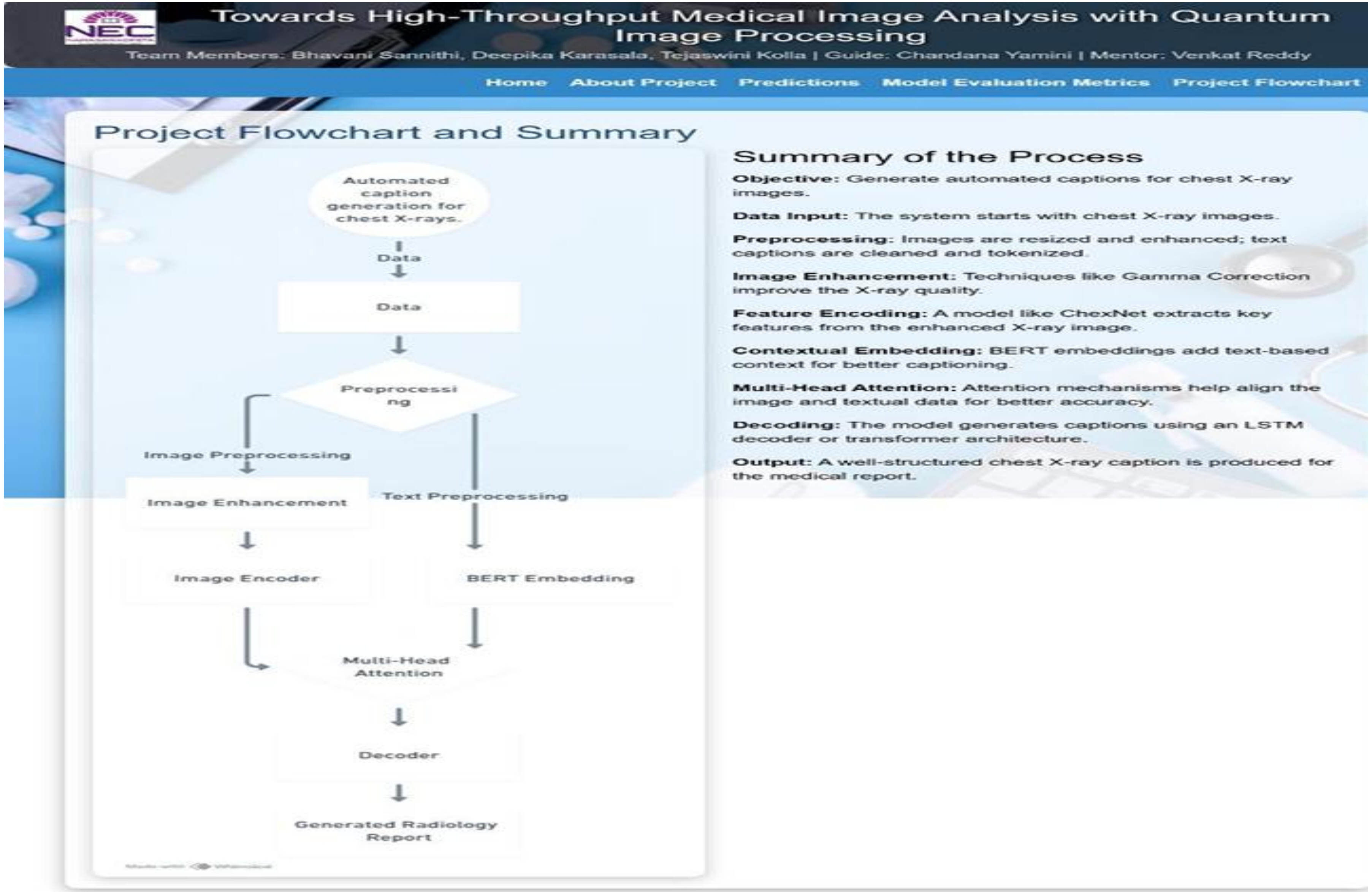
Model Evaluation Metrics

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. In summary, higher BLEU scores reflect better fluency and overall report quality.

Model	BLEU-1	BLEU-2	BLEU-3	BLEU-4	Impact on Radiology Report Generation
ChexNet-LSTM	1.0000	1.0000	0.4677	0.3162	Shows solid performance in generating structured medical reports, but improvement is possible with further image enhancement techniques.
ChexNet-LSTM + HE	1.0000	0.5677	0.4353	0.3162	Improved fluency and accuracy in the generated reports due to enhanced image features from Histogram Equalization (HE).
ChexNet-LSTM + CLAHE	1.0000	1.0000	1.0000	0.5623	The best performance in report generation accuracy and fluency, reflecting superior image enhancement from CLAHE.
CNN-LSTM + Multi-Head Attention	0.88	0.83	0.77	0.73	The highest fluency and structure in generated reports, leveraging attention mechanisms for better context capture.

OUTPUT SCREENS



CONCLUSION & FUTURE SCOPE

Conclusion

- Developed a deep learning model for automated radiology report generation.
- Integrated CheXNet-LSTM with CLAHE and MHA for improved performance.
- Achieved high BLEU scores, ensuring accurate caption generation.

Future Scope

- Enhance model generalization with larger datasets.
- Deploy in hospitals using cloud-based APIs for real-time use.
- Extend to detect multiple diseases in chest X-rays.

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QUESTIONS and ANSWERS

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Thank you for the opportunity to present our research on "Towards High-Throughput Medical Image Analysis with Quantum Image Processing." We appreciate our team whose contributions in bringing up this work, your interest in our work and are eager to contribute to advancements.

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Thank you