Visual Question Answering for Medical Images with Explainable AI

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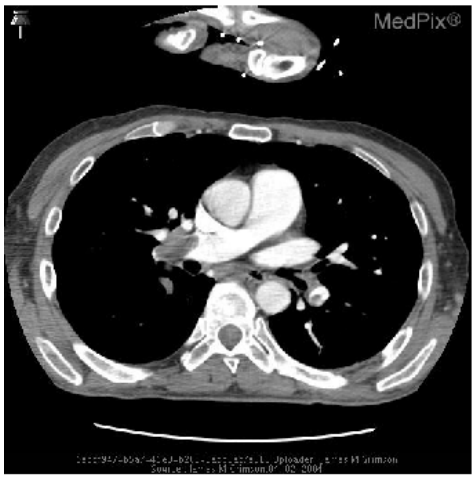
Second Review
March 25, 2023

What is Visual Question Answering and Explainable AI

- Visual Question Answering (VQA) is an emerging approach under the domains of Computer Vision and Natural Language processing, which aims to answer the user's question by analysing the given input image.
- Explainable AI (XAI) is a rapidly emerging research idea which refers to methods and techniques that helps us understand and interpret predictions made by AI models.



(g) **Q**: which organ system is shown in the ct scan? **A**: lung, mediastinum, pleura

(h) **Q**: what is abnormal in the gastrointestinal image? **A**: gastric volvulus (organoaxial)

Figure: Sample Images and Questions with Corresponding Answers from ImageCLEF 2019 VQA-Med Dataset

Problem Statement & Objectives

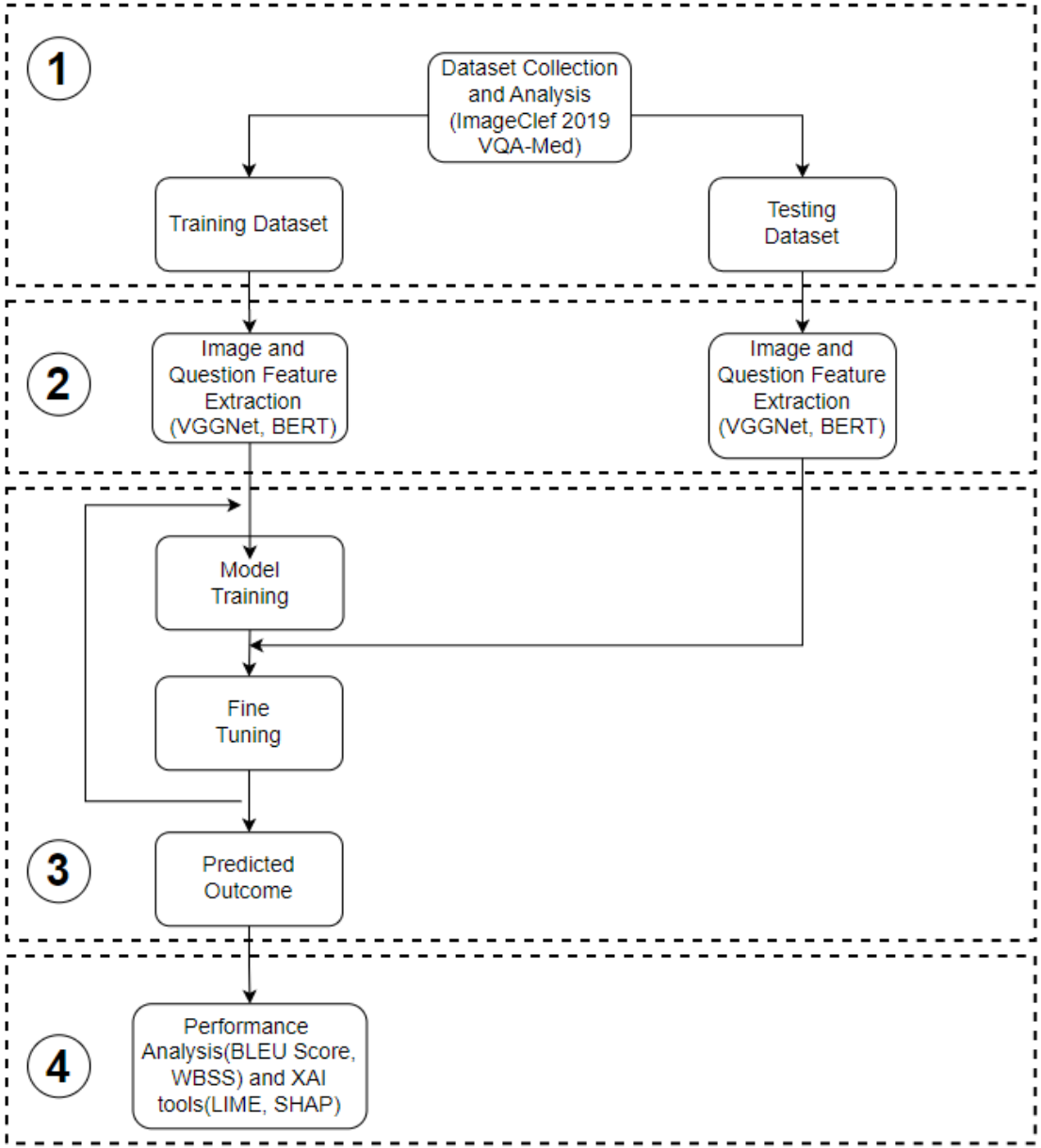
Problem Statement

- The aim of this project is to build an efficient VQA model that generates answers to questions related to medical images using deep learning techniques
- In addition, the reason behind the generated answer has to be analyzed using Explainable AI (XAI) tools such as LIME or SHAP to provide explanations on the outcome.

Objectives

- To collect and analyze the dataset of Visual Question Answering from the CLEF Forum.
- To build an efficient VQA model that generates the answers to the questions related to the given Medical Image using various transformer models like BERT, RoBERTa.
- To analyze the generated answer by using Explainable AI tools for providing explanations.

System Design & Module Split up



Module Split up:

1. Dataset Collection and Analysis
2. Feature Extraction
3. VQA Model Building
4. Performance Analysis using Quantitative measures and XAI

Review	Modules
Review 1	Dataset Collection and Analysis
	Image Feature Extraction
Review 2	Text Feature Extraction
	VQA Model Building
Review 3	Performance Analysis using Quantitative measures and XAI

Progress till Review 1

- In this Project, ImageClef 2019 VQA-Med dataset is used
- The dataset is collected and analyzed in terms of Modality, Plane, Organ and Abnormality. The result of analysis is given in the Table 1
- A custom CNN, a pre-trained VGGNet and VGGNet trained with our Organs data were compared for best best feature extraction from images
- Pre-trained VGGNet performed well compared with others.

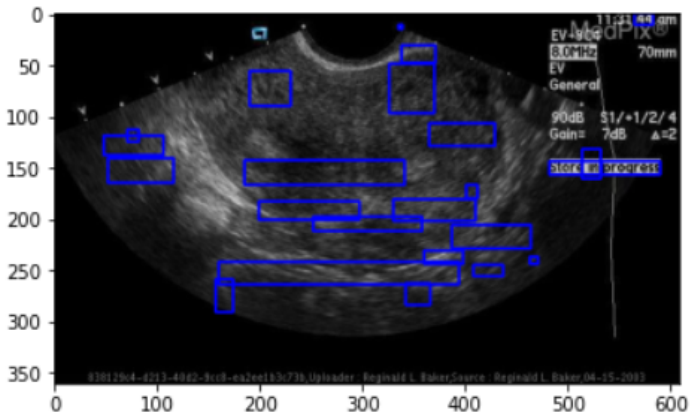
Dataset	**Question Category**	**No. of Questions**	**No. of Classes**
Training Dataset	Modality	3200	44
	Plane	3200	15
	Organ System	3200	10
	Abnormality	3192	1484
Testing Dataset	All	500	-

Table: Dataset Analysis

Review 1 - Follow up

S. No.	Question/Suggestions	Follow up
1	Use different CNN models for image feature extraction for different modality images	There isn't any increase in accuracy of the VQA model
2	Remove text from the image	Some of the organ features are also marked as text and removing the text would remove the features of the organ area in the image

Table: Review 1 - Follow up



Review 2 - Work Done (Feature Extraction)

- Image Features are extracted using VGGNet model
- The last layer of VGGNet is replaced with a Dense layer of 960 units
- When an image is fed to this model, the values at this newly added layer are the required image features
- A vocabulary is built using the text data available in the dataset
- This vocabulary is used with BERT-Tokenizer for tokenizing the question which is the required question feature

Token ID	**Token**
0	[PAD]
1	[UNK]
2	[CLS]
3	[SEP]
4	[MASK]
275	gastro
276	##intestinal
315	spine

Table: A sample set of tokens and their IDs from the vocabulary

Review 2 - Work Done (VQA Model Building)

- The question and image features are fused by concatenating them
- A BERT model is trained for answer generation using Masked Language Modeling (MLM) approach
- The BERT model is trained by masking the answer tokens associated with the concatenated image and question features
- The input for training the BERT model is of the form:

  [**CLS**] *IMAGE−FEATURE* [**SEP**] *QUESTION−FEATURE* [**SEP**] *MASKED−ANSWER* [**SEP**]

- Figure 2 shows the working of the BERT model to predict the masked word.

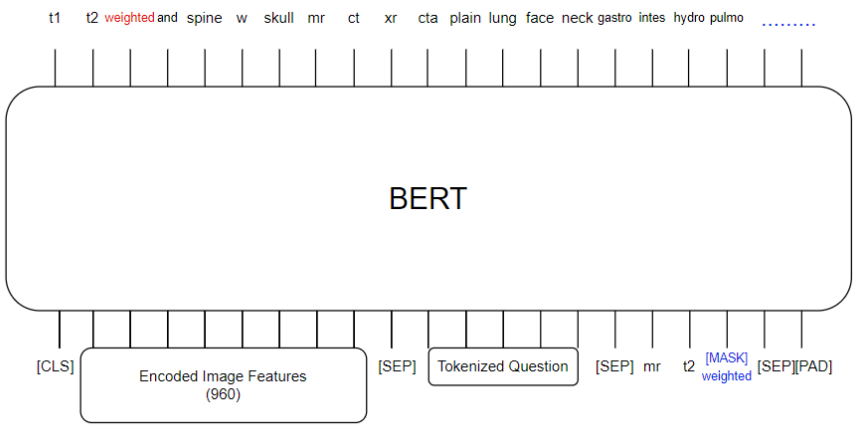


Figure: BERT model predicting the masked word

Review 2 - Work Done (Answer Generation)

- For generating answers from the trained model, the input data is of the form:

  [**CLS**] *IMAGE – FEATURE* [**SEP**] *QUESTION – FEATURE* [**SEP**] [**MASK**]

- For instance, to generate the answer **'bucket handle tear of meniscus'** (Image ID: synpic58267), the model generates answer as shown in the Figure 3

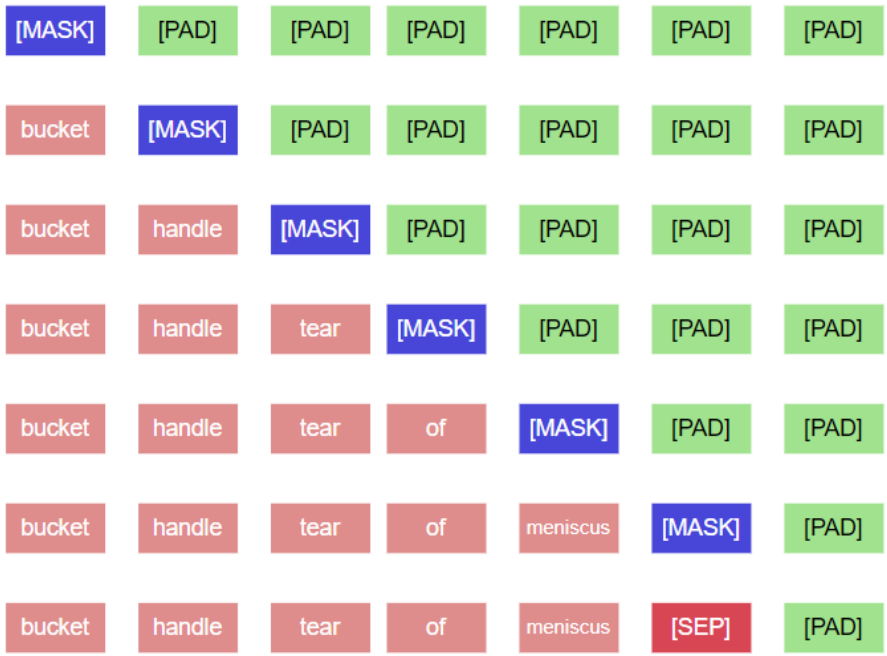


Figure: Answer Generation for a Sample with ID: synpic58267

Implementation & Result

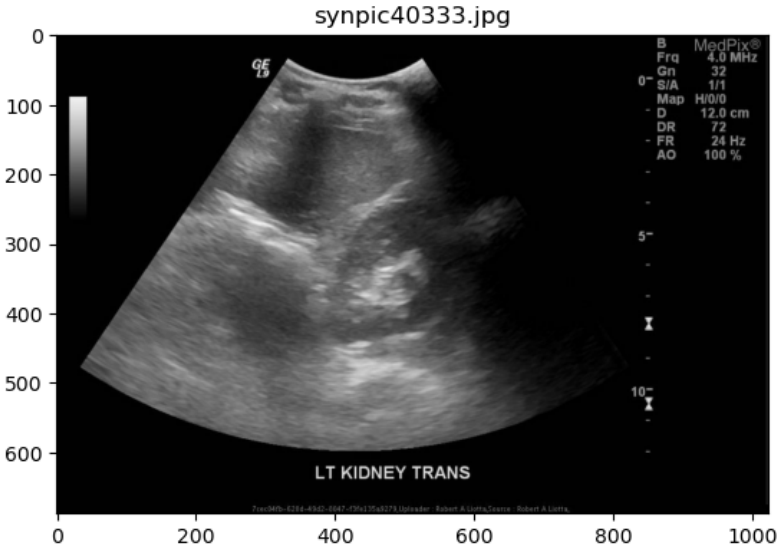
The performance of the VQA Model is analyzed using metrics such as accuracy, BLEU Score and WBSS. Table 4 shows the performance of the VQA model for each categories and overall test data.

Category	**No. of Samples**	**Accuracy**	**BLEU Score**	**WBSS**
Modality	125	65.6	68.79	71.66
Plane	125	64.8	64.8	65.35
Organ	125	50.4	53.19	54.82
Abnormality	125	6.4	7.65	12.03
Overall	**500**	**46.8**	**48.61**	**50.97**

Table: Performance analysis using Accuracy, BLEU Score and WBSS

Sample Answer Generation

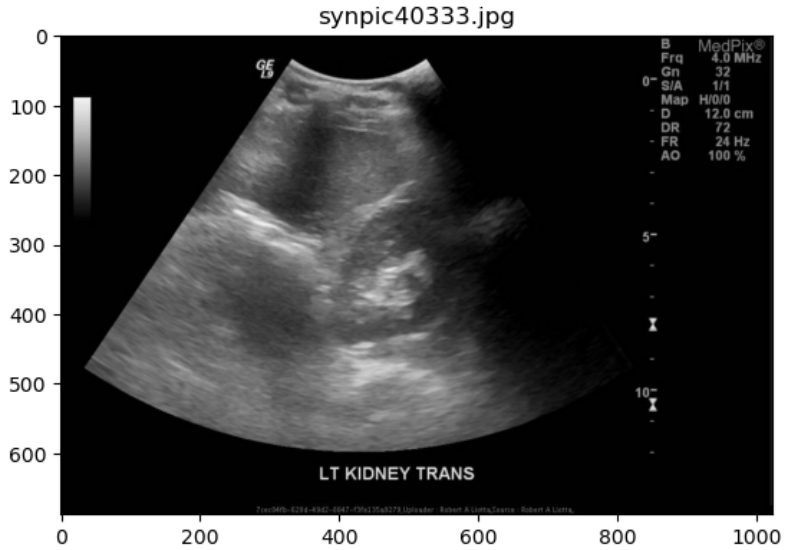
```
generateAnswer('synpic40333','what imaging modality was used to take this image?')
```




```
Generating Answers...
us
ultrasound
[SEP]

'us ultrasound '
```

```
generateAnswer('synpic40333','what organ system is imaged?')
```



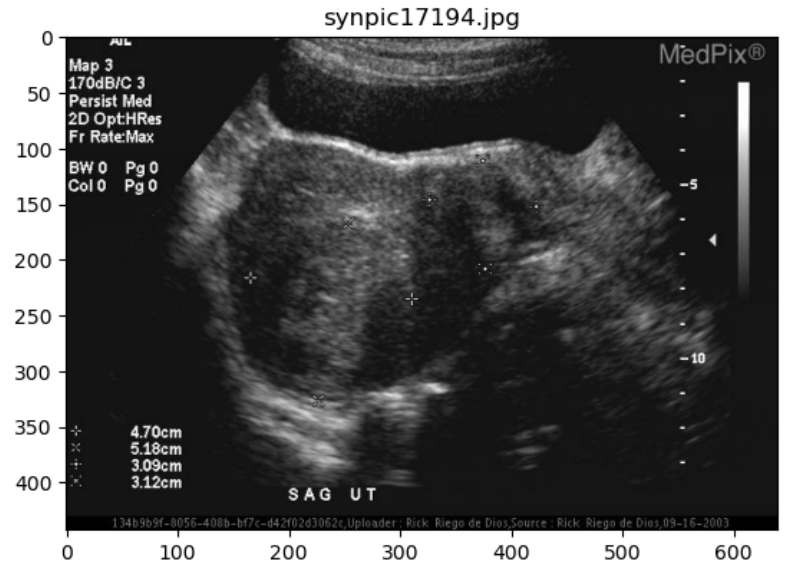

```
Generating Answers...
gastrointestinal
[SEP]

'gastrointestinal '
```

Figure: Sample Answer Generation of images of ID: synpic40333 queried about modality and organ. Both the answers are correct

Sample Answer Generation Contd.

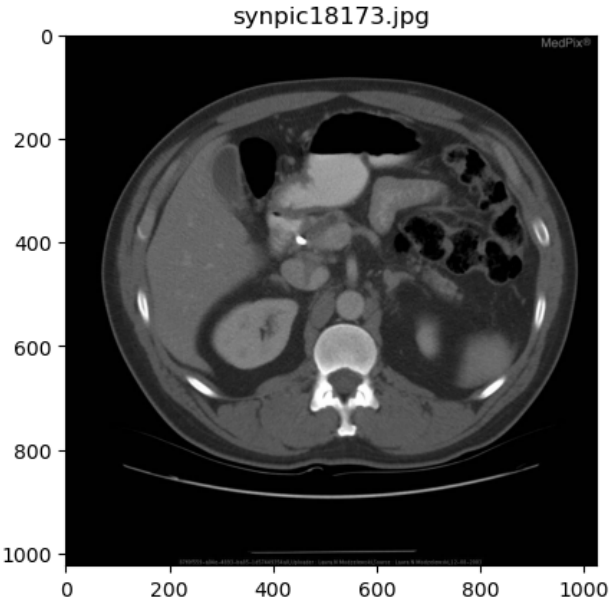
```
generateAnswer('synpic17194','what is the plane shown in this image?')
```




```
Generating Answers...
sagittal
[SEP]

'sagittal '
```

```
generateAnswer('synpic18173','what is the primary abnormality in this image')
```




```
Generating Answers...
pancreatic
adenocarcinoma
[SEP]

'pancreatic adenocarcinoma '
```

Figure: Sample Answer Generation of images of ID: synpic17194 and synpic18173 queried about plane and abnormality. The plane is correct but the abnormality is worng. Actual answer is **pancreatic duct adenocarcinoma**

Explainable AI (XAI)

- There are many XAI tools available like LIME, What-If, SHAP, ELI5, Grad-CAM etc.,
- In this project, LIME and SHAP tools are to be used
- **LIME** - **L**ocal **I**nterpretable **M**odel-Agnostic **E**xplanations
  - outputs a list of explanations, reflecting the contribution of each feature to the prediction of a data sample
  - takes a prediction function of a model as input along with a single input data for the model
  - data set is created by taking all the features from the single input data and fits a interpretable model locally on the created perturbed dataset
  - produces an analysis of how the model arrives at the result for the input data by analyzing the prediction function's working
- **SHAP** - **SH**apley **A**dditive ex**P**lanations
  - explains how the different features affect the output or what contribution do they have in the outcome of the model
  - takes a prediction function and a set of data as input and try to find the SHapley values that expresses model predictions as linear combinations of binary variables

Conclusion

- The dataset for the task of Visual Question Answering is collected and it is analyzed
- The image and question features are extracted using VGGNet and BERT. The features are fused by concatenation.
- A BERT model is built and trained for Answer Generation by Masked Language Modeling
- The trained model is used for generating answers for the test data which resulted in 46.8% Accuracy, 48.61 BLEU Score and 50.97 WBSS Score.
- The performance of the trained VQA model is low for Abnormality based question, due to the lack of data enough for 1484 classes of abnormality.
- In future, XAI techniques are to be applied to generate explanations for the predicted outcome.
- Also, the VQA model can be fine tuned for increasing the accuracy of abnormality based question

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Thank You

Literature Survey

Paper Title	Methodology	Limitations
CGMVQA: A New Classification and Generative Model for Medical Visual Question Answering [**CGMVQA**]	**Dataset**: ImageCLEF 2019 VQA-Med **Image Feature Extraction**: ResNet-152 **Question Feature Extraction**: BERT Tokenizer **Answer Generation**: BERT **Analysis**: Accuracy-62.4, BLEU Score-64.4	The proposed solution for VQA is building different models for different types of question such as Modality, Plane, Organ and Abnormality. But in reality, the exact type of a question may not be known.
Visual question answering in the medical domain based on deep learning approaches: A comprehensive study [**Al-Sadi**]	The Questions are classified into 4 categories and multiple models are trained for each type of question **Dataset**: ImageCLEF 2019 VQA-Med **Image Feature Extraction**: VGGNet16 **Answer Generation**: Ensemble of Classification models **Analysis**: Accuracy-60.8, BLEU Score-63.4	All models built for each question categories are classification models which is completely a black-box approach

Literature Survey Contd.

Paper Title	Methodology
Explainable Artificial Intelligence for Human Decision Support System in the Medical Domain [**XAI-CNN**]	**Dataset:** Red Lesion Endoscopy data **XAI tools:** LIME, SHAP, CIU A CNN is trained using the dataset. XAI tools are then used for visualization in terms of heatmap. The result of visualization is then compared
Grad-CAM: Visual Explanations from Deep Networks via Gradient-based Localization [**Grad-CAM**]	Proposed Gradient-weighted Class Activation Mapping (Grad-CAM) for explaining and understanding CNN based models. This technique helps to visualize the important regions on the input image, that corresponds to the predicted outcome. This technique helps to understand many CNN-based models such as Image-Captioning and VQA models.
LISA : Enhance the explainability of medical images unifying current XAI techniques [**XAI-LISA**]	**Dataset:** COVID-19 Dataset **XAI tools:** LIME, SHAP, Anchors **Other XAI techniques:** Integrated Gradients Transfer Learning is used for the detection of COVID-19. The XAI tools LIME, SHAP Anchor and Integrated Gradient techniques' results are combined to give explanations.