Visual Question Answering for Medical Images with Explainable Al

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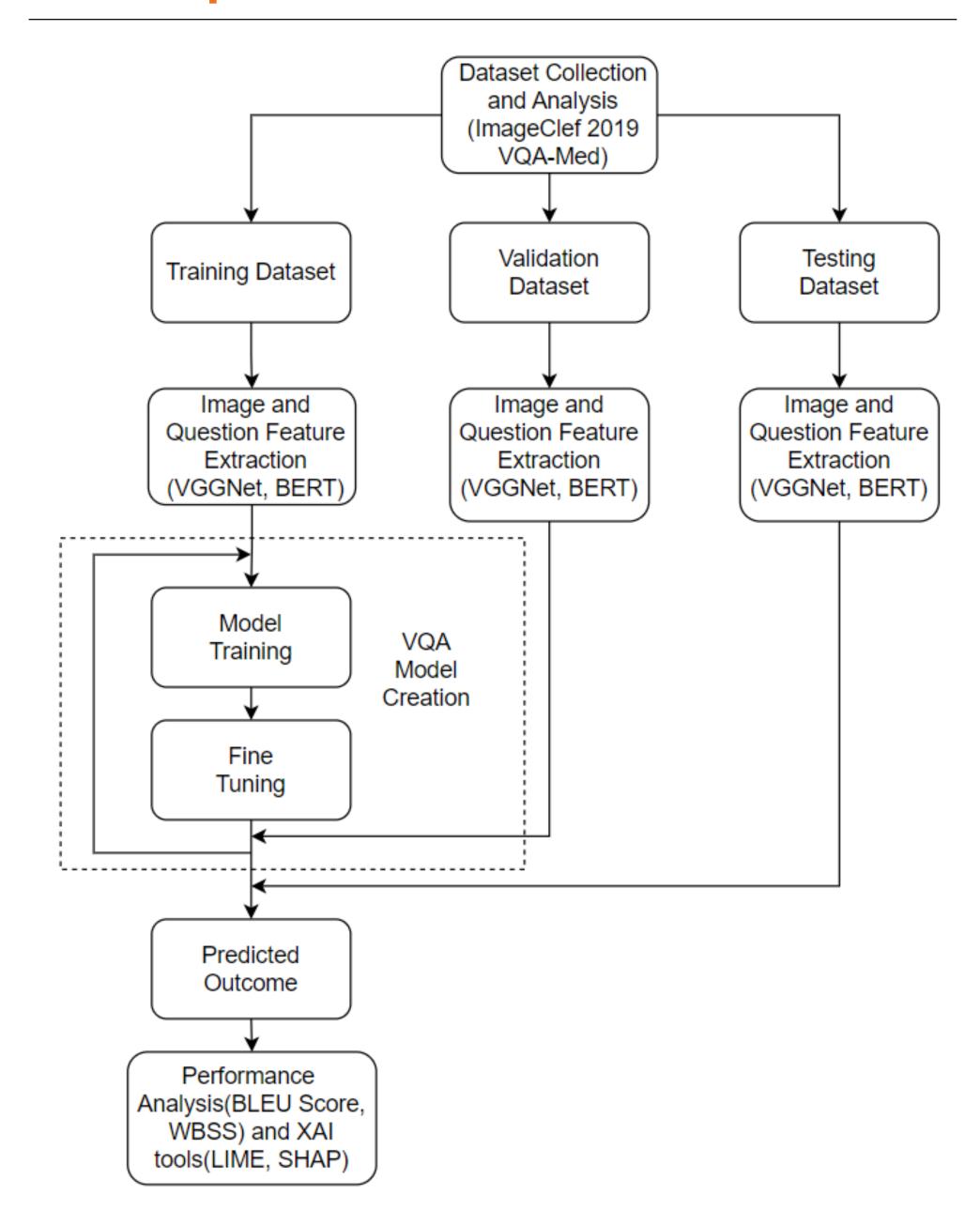




Highlights of Proposed Model

- To collect and analyze the ImageCLEF 2019 VQA-Med dataset
- To build an efficient VQA model that generates the answers to the questions related to the given Medical lmage
- To analyze the generated answer using XAI techniques, LIME and SHAP for explanations

Proposed Model for VQA with XAI



Performance Analysis of VQA model

Question	No. of	Accuracy	BLEU Score	WBSS
Categories	Samples			
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

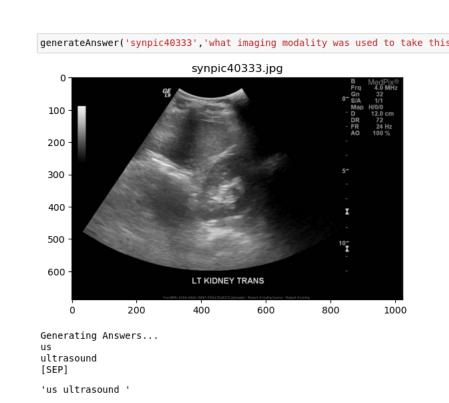
Functional Modules and Dataset Description

- Dataset Analysis
 - Categories of Questions (Modality, Plane, Organ, Abnormality)
 - Classes of Answer under each category of question
- VQA Model Building
 - Image Feature Extraction using VGGNet
 - Question Feature Extraction using BERT Tokenizer
 - Answer Generation using BERT
- Performance Analysis of VQA model using Quantitative Metrics (Accuracy, BLEU Score, WBSS)
- Interpreting VQA model using XAI techniques LIME and SHAP

Dataset	Images	Question		No. of
		Category	Questions	Classes
Training	3200	Modality	3200	44
		Plane	3200	15
		Organ System	3200	10
		Abnormality	3192	1484
		Total	12792	1553
Validation	500	Modality	500	35
		Plane	500	15
		Organ System	500	10
		Abnormality	500	413
		Total	2000	473
Testing	500	All	500	166

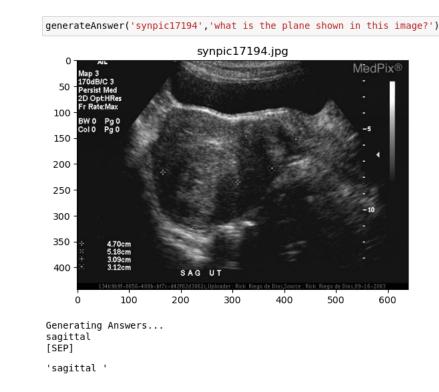
Answer Generation using developed VQA model

Modality based question



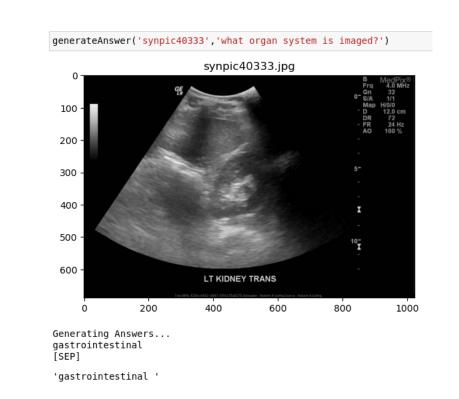
Answer generation for the image (ID: synpic40333) queried about modality

Plane based question



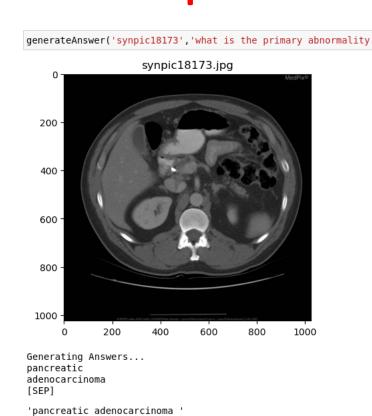
Answer generation for the image (ID: synpic17194) queried about plane

Organ based question



Answer generation for the image (ID: synpic40333) queried about organ

Abnormality based question

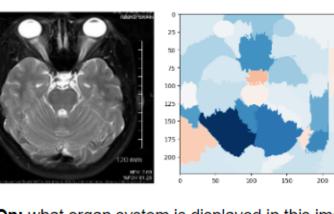


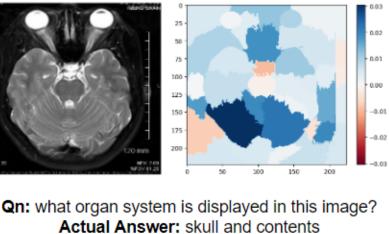
Answer generation for the image (ID: synpic18173) queried about abnormality

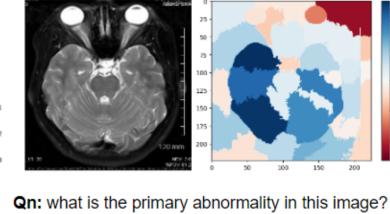
VQA Model Interpretation using LIME and SHAP

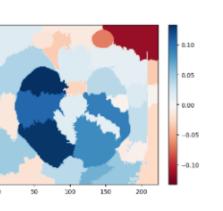
VQA Model Interpretation using LIME

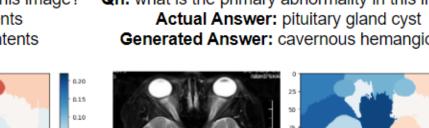
Image ID: synpic56918 **Qn:** what type of imaging modality is shown? **Qn:** What is the plane of this image? Actual Answer: mr t2 weighted Actual Answer: axial Generated Answer: axial Generated Answer: mr t2 weighted





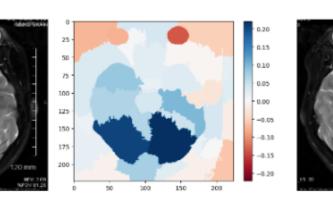


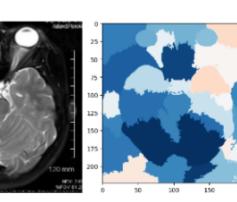


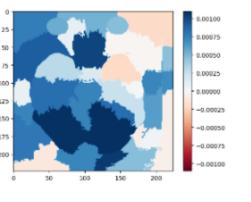


LIME explanations for a sample image (ID: synpic56918) for four

different questions of different categories



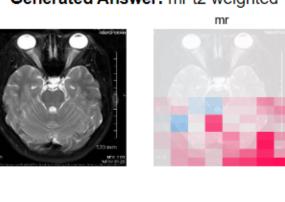




VQA Model Interpretation using **SHAP**

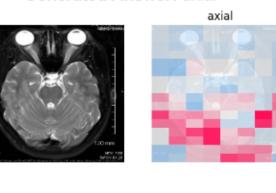
Image ID: synpic56918 Qn: What is the plane of this image?

Qn: what type of imaging modality is shown? Actual Answer: mr t2 weighted Generated Answer: mr t2 weighted



-0.00015-0.00010-0.00005 0.00000 0.00005 0.00010 0.00015





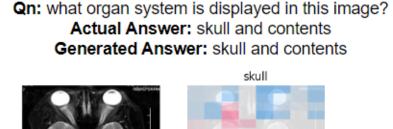
Actual Answer: axial

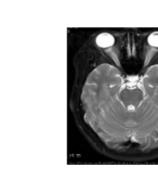


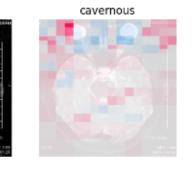
Qn: what is the primary abnormality in this image?

Actual Answer: pituitary gland cyst

Generated Answer: cavernous hemangioma







-0.00010 -0.00005 0.00000 0.00005 0.00010

SHAP explanations for a sample image (ID: synpic56918) for four different questions of different categories

Inferences

- The proposed VQA model resulted with 46.8% Accuracy, 48.61 BLEU Score and 50.97 WBSS
- The accuracy is low due to less number abnormality samples in the training set, compared to number of abnormality classes (1484 classes)
- XAI techniques LIME and SHAP are applied to analyze and interpret the predicted outcome
- Both LIME and SHAP modify the input images by inpainting some segments or partitions and computes the impact on the output of the model

LIME

- A local surrogate model is built for generating explanations
- It builds the local interpretable model using the perturbed dataset and the explanations generated are inconsistent for each turn depending upon the perturbed dataset created
- Also, it takes more time to generate explanations and it depends on the number of samples in the perturbed dataset

SHAP

- The impact of modifications on the input is measured in terms of Shapley values
- It calculates the Shapley values for the set of features which represents the contribution of that set of features towards the output
- The Shapley values of the set of features are averaged to get the global contribution of each feature

References

- Ben Abacha Asma, Hasan Sadid, Datla Vivek, Liu Joey, Demner-Fushman Dina and Müller Henning, (2019) VQA-Med: Overview of the Medical Visual Question Answering Task at ImageCLEF 2019, CLEF 2019 Working Notes, CEUR Workshop Proceedings 2019, https:// ceur-ws.org/Vol-2380/paper_272.pdf.
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- Marco Tulio Ribeiro, Sameer Singh and Carlos Guestrin, (2016) "Why Should I Trust You?": Explaining the Predictions of Any Classifier. In Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Demonstrations, pp. 97-101, https://doi.org/10.18653/v1/N16-3020.
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