Visual Question Answering for Blind People

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1 Task Definition

In this project, we will use VizWiz dataset (Gurari et al., 2018) to address the visual question answering for blind people. The high level task of our project is to predict an accurate answer to a visual question given an image and question about it.

1.1 Subtasks

We will break down the task into the following three specific subtasks. Given the questions are collected from blind users of a mobile phone application, most of them are conversational and may not be answerable. Therefore, our first subtask would be to identify whether a question is valid and answerable according to the given image. The second task would be to output the correct answer if the question is answerable. Since every question in the VizWiz dataset has 10 answers, it is also important to determine how to select or combine these answers during training, which will be our third subtask.

1.2 Input-output Representation

Limited by computing resources, we would not try to modify any pre-training mechanism. Therefore, we would seek to incorporate task-specific knowledge to augment current large pre-trained model to boost performance. Specifically, according to our data analysis, we would like to address image framing issue particularly for images with text detected. Further discussion will be put into later sections.

Following (Tan and Bansal, 2019) and (Chen et al., 2020)'s work, we would like to use both joint representation and coordinated representations. Our tasks would be to generate two embeddings separately for images and texts, and a cross-modality output for their joint representation.

*Everyone Contributed Equally – Alphabetical order

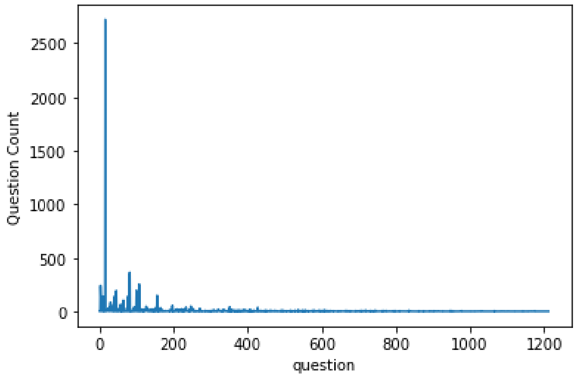

Figure 1: Question Frequency Distribution

For image representation, we would follow (Anderson et al., 2018). The input image embedding would be the features (positions and Region of Interest) of detected objects in it.

For language representation, the input would be word-level sentence embedding tokenized by WordPiece as in BERT (Devlin et al., 2019).

2 Data Analysis

2.1 Analysis of Questions

We examine the questions in both sentence and word level. We first calculate the distribution of the questions and observe that the percentage of questions that appear more than once is 54.4%. "What is this?" is the most common question that occupies more than 13% of all questions while the second most common question "What color is this?" is only about 1.7%. The frequency distribution is shown in Figure 1. We also analyze question diversity by computing statistics on sentence lengths. The mean question length is 6.76 words and the 25th and 75th percentile lengths are four and eight words respectively. The longest question has 62 words and the shortest one has only two words.

We also analyze the words in each sentence. We

Figure 2: Answer popularity word cloud excluding ”unanswerable” and ”unsuitable image” answers

consider the words that appear only once in all questions as rare words, which are about 2.64% of all words. The percentage of questions having at least one rare word is 12.09%. The most common first word of each question is ”What”, which is consistent with the observation of most common questions in the sentence-level analysis. We also observe that the questions in this dataset often begin with a rare first word. The percentage of questions starting with a first word that occurs for less than 5% and 10% of all questions is 32.68% and 38.24% respectively.

2.2 Analysis of Answers

We first analyze the percentage of answerable questions. Since VizWiz (Gurari et al., 2018) images are collected by blind people, a large portion of images have low quality and hence are not answerable. Based on our analysis, only 73.04% of visual questions are tagged as answerable.

We also analyze the diversity of answers by calculating statistics on answer length. The mean and median answer lengths are 1.66 and 1.00 words respectively, and the max answer length is 21 words. The result indicates that the visual questions in dataset tend to have short answers. We also generate a word cloud computed on all answers in the dataset excluding ”unanswerable” and ”unsuitable image”, which is shown in Figure 2.

Lastly, we analyze the answer confidence level and agreement level. There is a total of 20523 questions in the dataset. Each question has 10 answers, and each answer has a confidence level ranging from ”yes”, ”maybe” to ”no”. Among all questions, there are 18.82% questions have all 10 answers with a confidence level of ”yes”, 57.02% questions have at least 8 answers with a confidence level of ”yes” and 94.85% questions have at least half of the answers with a confidence level of ”yes”.

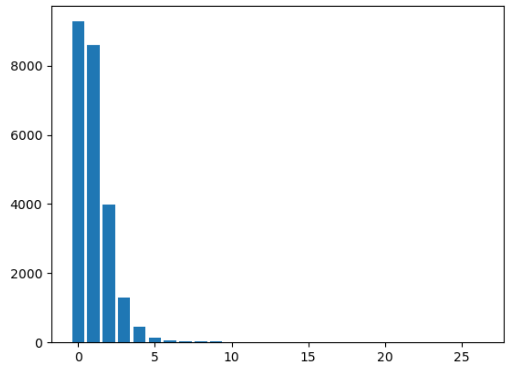

Figure 3: Number of bounding boxes

The dataset also has a pretty high human agreement level. Although we use a very strict agreement measure (exact string matching), we still observe that 40.54% of visual questions have more than 5 people agreed on the most popular answer, and 73.20% of visual questions have more than 3 people agreed on the most popular answer.

2.3 Analysis of Images

We run pre-trained YOLO (You Only Look Once) v3 model (Redmon et al., 2016) as a naive, coarse-grained, first-step baseline to analyze the training images. The weights of the model have been obtained by training on COCO dataset (Lin et al., 2015), and we hereby adapt the setting, trying to detect objects from 80 classes.

We count the number of bounding boxes on each image after we run objectness score thresholding and Non-Maximum Suppression to avoid overlapping. We observe that, we get 24,480 bounding boxes in total, and most images have either 0 (9,280 out of 23,953) or 1 (8,609 images) bounding box. The average number of bounding boxes per image is 1.02, and the third-quartile count is 2.0. The bar graph is shown in Figure 3.

After investigating the generated bounding boxes with labels, we observe that YOLO detects ”Person” and ”Bottle” objects most often. We also find that the coarse-grained model classify human hands as ”Person” in most cases, and the 80 classes in COCO dataset are obviously insufficient.

From the experiment of running YOLO we conclude that, though most images may only contain one major object, it is difficult to successfully detect it. Ultrafine-grained semantic labels might be needed. Further study could be conducted when

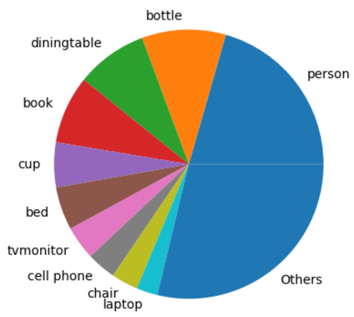

Figure 4: Predicted Classes Distribution

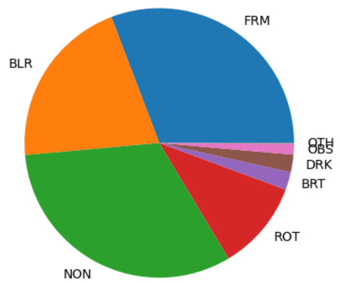

Figure 5: Images with Flaws Distribution

we incorporate the labeled image captions to our current predictions, to check where most errors are from. And we will adopt more advanced method such as Faster R-CNN (Changpinyo et al., 2019) to further explore the image data.

Apart from object detection bounding boxes analysis, we also analyze image quality. We observe that, a large number of pictures are covered by hands and many pictures are blurred. We then only focus on images that are tagged ”answerable,” and we find among 19,873 images that score 1 or below for category ”recognizable,” 52% of them have the ”frame” flaw. Figure 5 shows the pie chart of flaws.

3 Related Work and Background

3.1 Related Tasks

Over the years, there has been rapid progress in bridging vision and language in the research community. Various models have been developed and applied to a wide range of vision-and-language tasks. We'll briefly describe the problem and training objective of five well-established tasks and include relevant papers.

Visual Question Answering (VQA) has received a lot of attention in recent years. A natural language question regarding an image is presented and the model will output the correct answer to it. Various models are proposed for this specific task (Agrawal et al., 2016; Tan and Bansal, 2019; Ben-younes et al., 2017; Fukui et al., 2016).

Visual commonsense reasoning (VCR) is similar to VQA, but besides predicting the answer, the model is also expected to select the correct answer justification among multiple choices (Lu et al., 2019; Li et al., 2019; Tan and Bansal, 2019).

Visual grounding (VG) aims to localize an image region or object given a natural language question. Common approaches to this task including bounding box proposals and reranking a set of image region candidates (Lu et al., 2019; Li et al., 2019; Fukui et al., 2016; Yu et al., 2018).

Image captioning recognizes the context of an image and adds a descriptive sentence to it. Models targeting this task are mainly attention-based neural networks that could extract deep features (Anderson et al., 2018; Donahue et al., 2016; Xu et al., 2016).

Image-text matching aims to measure the visual-semantic similarity between a text and an image. It has been widely applied to other applications such as image search for a given query (Kim et al., 2018; Nam et al., 2017).

Besides these five tasks, there are also many other popular vision-and-language transfer tasks such as caption-based image retrieval (Lu et al., 2019) and emotion recognition and sentiment analysis (Delbrouck et al., 2020).

3.2 Related Techniques

In this section, we briefly review the techniques used in previous related work with a focus on the feature representation, attention mechanisms and fusion methods.

3.2.1 Feature representation

Generating feature representation has been a crucial step in transforming raw data to meaningful features. There has been substantial past works in developing single modality models separately for vision and language representations. For image representations, common backbone models include Faster R-CNN (Ren et al., 2016), R2+1D-(152)

(Tran et al., 2015), VGG (Simonyan and Zisserman, 2015), ResNet (He et al., 2015) and fishNet (Sun et al., 2019). In terms of language representations, BERT (Devlin et al., 2019), a transformer language model pretrained on the BookCorpus (Zhu et al., 2015) and English Wikipedia is a popular choice nowadays.

Language embeddings and image embeddings are then combined through summation or multiplication (Lu et al., 2019; Delbrouck et al., 2020) to form a joint representation for fine tuning at a later stage. Another common approach to generate joint representation involves early fusion of image and text. Models are pretrained with multi-modal objectives such as masked language modeling with image and sentence-image prediction (Lu et al., 2019; Li et al., 2019; Tan and Bansal, 2019) to directly generate joint representations.

3.2.2 Attention Mechanism

Attention mechanism has been proven effective in many tasks including VQA. Previous attention approaches commonly used in VQA or related tasks can be classified into following four categories:

- Self attention that aggregate information inside each modality by query-key-value attention mechanism (Vaswani et al., 2017).

- Question-guided visual attention (Xu et al., 2016; Xu and Saenko, 2016) that compute attention on image region.

- Co-attention that jointly reason about both question and visual attention to interact across the two modalities. It uses image representation to guide the question attention and question representation to guide image attention (Lu et al., 2017, 2019; Yu et al., 2019). There also exist many variants of co-attention such as bilinear attention (Kim et al., 2018) and dense co-attention network (DCN) (Nguyen and Okatani, 2018) that considers interactions between every pair of question words and image regions.

- The intra- & inter-modal attention (DFAF) (Peng et al., 2019) that consider both inter-modality attention and intra-modality attention, where attention for intra-modality feature aggregation is dynamically modulated by the other modality using the pooled features.

3.2.3 Fusion Methods

The common multi-modal fusion approach is that visual and language features are extracted from the image and question independently as the first step, and then they are fused to compute the final results.

In previous studies, many works employed simple fusion methods that use element-wise product or summation of the visual and language features as final fused feature, and fed it to fully connected layers to predict results. (Lu et al., 2019; Delbrouck et al., 2020)

More complex fusion techniques have also been explored. For instance, Multimodal Compact Bilinear pooling (MCB) (Fukui et al., 2016) uses bilinear pooling method to compute the outer product between visual and language vectors as their fusion. In contrast to element-wise product approach, MCB allows a multiplicative interaction between all elements of both vectors. MUTAN fusion model (Ben-younes et al., 2017) is able to represent full bilinear interactions between visual and language modalities using Tucker decomposition of the correlation tensors, while maintaining the size of the model tractable. Multi-modality Latent Interaction Network (MLIN) (Gao et al., 2019) first encodes question and visual features into latent summarization vectors and then it go through the process of interaction, propagation and aggregation to achieve multi-modality reasoning.

4 Baselines

4.1 Model Selection

We would run the following 4 models as baselines.

- LSTM+CNN (Kazemi and Elqursh, 2017) uses CNN to extract image features and uses LSTM for question embedding. Multiple attention distributions are computed over the spatial dimensions of the image features. Then the concatenation of image feature glimpses and the state of the LSTM is fed to two fully connected layers.

- LXMERT (Tan and Bansal, 2019) constructs separate representations for images and texts, use (Anderson et al., 2018) for images. Have two encoders each for one modality with self-attention, and then a cross-modality encoder with cross-attention.

- Pythia (Singh et al., 2019) proposes Look,

Method	Binary (yes/no)		Number		Nonanswerable		Overall		
	acc	edit dist	acc	edit dist	acc	edit dist	total	acc	edit dist
LSTM+CNN	**66.42%**	7.14	**30%**	8.64	**83.02%**	6.42	4319	**48.97%**	9.05
PYTHIA	**77.49%**	5.27	**32.24%**	7.77	**87.32%**	5.5	3171	**54.77%**	8.05
LXMERT	**72.73%**	5.40	**23.81%**	9.34	**86.56%**	5.53	3171	**52.24%**	8.30

Table 1: Performance results for models in different question categories.

Read, Reason, Answer mechanism, use spatial attention, lstm and OCR in the model.

Since their pre-trained models are all available and we are interested in how their different attention / representation / fusion methods would effect the performance. Their overall results on VizWiz dataset are listed in table 1. All metrics follow VizWiz official setting, i.e.

$$accu = min(1, \frac{\textit{\# humans that provided that answer}}{3})$$

We are particularly interested in each model's performance with flawed images, and we mainly focus on binary (yes or no) questions and questions related to numbers. From VizWiz challenge leader board we observe that current SoTA model achieves 56.33% accuracy, but most models have relatively weaker performance in answering questions related to "numbers," with only 27.1% accuracy. We first aim to explore this discrepancy.

According to our data analysis, many input images are flawed. Blurring and framing issues are the most common types of flaw. Therefore, we expect to produce model results for each sub-category of image quality issues.

Aiming to boost performance with flawed images, we would test different fusing methods that inject de-noising technique, such as applying multi-stage progressive image restoration (Zamir et al., 2021) to our baseline models. Additionally, We would evaluate alternative representation / encoding / fusion methods following VizWiz official evaluation metric.

4.2 Baseline Implementation Details

4.2.1 LSTM+CNN

We ran a variant of model described in "Show, Ask, Attend, and Answer" paper (Kazemi and Elqursh, 2017) referencing github [1]. Visual features are extracted using a pretrained ResNet-152 model on ImageNet. Questions are embedded and encoded with LSTM. Image features and question embedding are then combined to compute multiple attention distributions over image features. The attended image features and the questions are concatenated and fed into two fully connected layers. We trained model for 40 epochs with batch size 128 and learning rate 0.001.

4.2.2 LXMERT

We ran LXMERT referencing github [2] to run Vizwiz Dataset. We used the image representation extracted using Faster-RCNN and sentence representation extracted using Bert. Following the original paper (Tan and Bansal, 2019), we finetuned the model for 20 epochs with batch size 32. The validation accuracy calculated using the formula in the paper and the formula on Vizwiz website is 54.46% and 52.24% respectively. We also calculated the average edit distance between the output answer and all the answers provided by crowd workers as an intrinsic evaluation of the baseline model.

4.2.3 Pythia

We used Pythia pretrained model (Singh et al., 2019) on vizwiz and VQA2.0 available online [3] to run inference on vizwiz visual question answering validation dataset.

4.3 Error Analysis

We defined an output answer to be incorrect if it doesn't equal to the most popular answer provided by the 10 crowd workers. Following the metric given on Vizwiz website, we also break down the questions into the following categories for more detailed error analysis:

1. Binary: if at least three reference answers are either "yes" or "no".
2. Number: if at least three reference answers are numbers. We define an answer as number if it is either an integer, float or double without any other characters.

[1]https://github.com/DenisDsh/VizWiz-VQA-PyTorch

[2]https://github.com/airsplay/lxmert

[3]https://github.com/allenai/pythia

Method	Binary (yes/no)			
	yes/no swapped	unanswerable	question begins with ”can you ..”	question length stats
LSTM+CNN	31%	50.38%	19.38%	max: 157 min: 10 ave: 51
PYTHIA	54.5%	29.3%	17.2%	max: 160 min: 12 ave: 44
LXMERT	**63.33**%	25%	18.33%	max: 160 min: 13 ave: 44
Method	Number			
	% of non-numbers	unanswerable	question begins with ”can you ..”	question length stats
LSTM+CNN	76.66%	60%	10%	max: 129 min: 9 ave: 44
PYTHIA	68.8%	41.6%	10%	max: 129 min: 9 ave: 44
LXMERT	80%	63.63%	9.1%	max: 129 min: 9 ave: 41
Method	Nonanswerable			
	% of binary	% of numbers	question begins with ”can you ..”	question length stats
LSTM+CNN	9.75%	1.26%	7.55%	max: 249 min: 8 ave: 228
PYTHIA	11.8%	0.9%	6%	max: 206 min: 9 ave: 147
LXMERT	12%	0.47%	5.23%	max: 206 min: 9 ave: 130

Table 2: Error analysis of models' incorrect outputs on different question categories.

3. Unanswerable: if at least three reference answers are unanswerable.

The overall accuracy for LSTM+CNN, LXMERT and PYTHIA is 48.97%, 52.24% and 54.77% respectively. The average edit distances for all models are around 8-9. Please see table 1 for detail test results.

For incorrect outputs on each of the above question categories, we conducted error analysis in terms of their questions and images. Question analysis is performed on every model, however due to limited computational resource, we're unable to run LXMERT and PYTHIA on the new dataset with image quality issue labels, therefore image quality analysis is only performed on LSTM+CNN. Please see table 2 for test statistics of each question category.

4.3.1 Question Analysis

Binary questions constitute 6.34% of the total dataset, and the baseline models' accuracy is about 66-73%. We first analyzed the number of workers that agreed on the incorrect output answer, since 10 workers themselves often give different reference answers. Figure 6 is the plot for the distribution of wrong answer votes for each model. We can see a similar pattern for all of the models, which the majority of incorrect answers completely different from all the reference answers provided by the crowd workers (0 votes mean that no worker give the same reference answer as the output answer).

However, it's interesting to note that LXMERT is able to identify 63.3% of the binary questions but output opposite answers while LSTM+CNN only outputs ”yes” or ”no” for binary questions 31% among all. Moreover, LSTM+CNN outputs ”unanswerable” twice as much as LXMERT and PYTHIA on binary questions and these statistics indicate that LXMERT and PYTHIA performs better than LSTM+CNN on binary questions, possibly due to their deeper model architecture. We also noticed that about 18% of the incorrect binary questions begin with ”can you”, which might lead the crowd workers to answer ”yes” or ”no” while the expected answer is something else. This might be a potential dataset issue and we would explore ways to eliminate such bias in our improvement.

Number questions only constitute 1.63% of the total dataset, and the baseline models' accuracy is about 23-30%. We also analyzed the number of workers that agreed on the incorrect output answer and similarly to binary questions, more than 65% of the output answer doesn't exist in the workers reference answers. 80% of LXMERT's incorrect answers are non numbers while the percentage for PYTHIA is 68%, which might indicate that PTYHIA perform slightly better than the other models on binary questions. All three models tend to output ”unanswerable” to number questions, failing to recognize the numbers in the image.

Unanswerable questions constitute 25.6% of

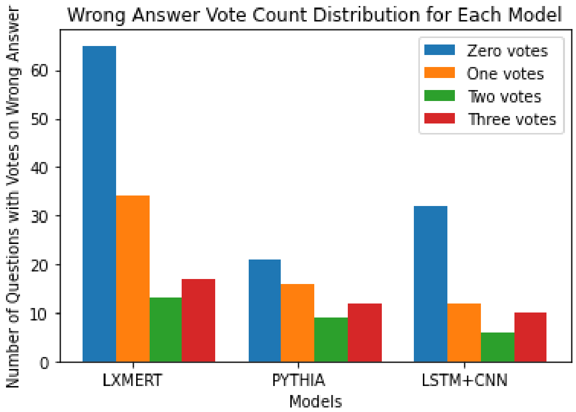

Figure 6: Wrong Answer Vote Count Distribution on Binary Questions

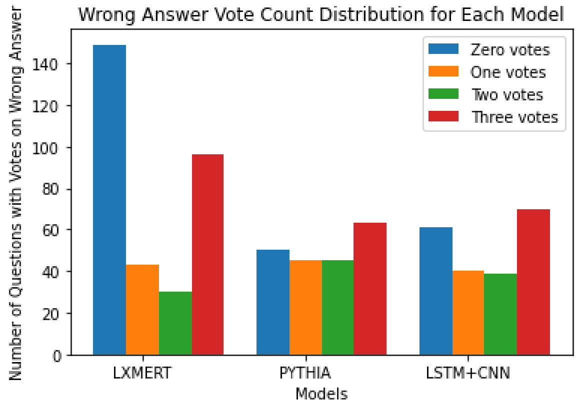

Figure 7: Wrong Answer Vote Count Distribution on Unanswerable Questions

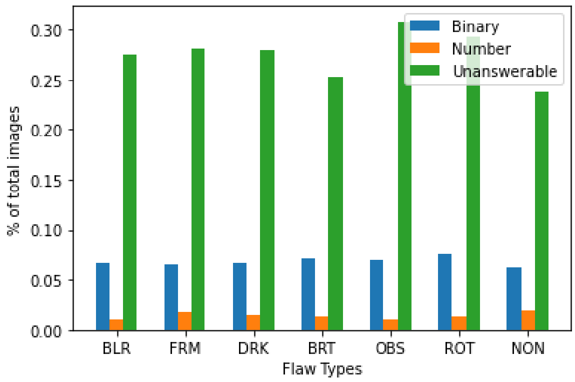

Figure 8: Image flaw type percentage based on different question types

the total dataset, and the baseline models' accuracy is above 83%. We can see from Figure 7 that the number of workers who agreed on the incorrect answer's distribution is much more even compared to that of binary and number questions, indicating that most workers may tend to give "unanswerable" as reference answer and might lead the models to favor "unanswerable" as answer. This might be a bias in the dataset and we would like to explore ways to eliminate such bias such as removing them from the training dataset if "unanswerable" is not the most popular answer. We're also interested in the models' ability to distinguish different kind of questions and from the result in table 1, we can see that 10% of the incorrect answers for unanswerable questions are binary while only about 1% are number. LXMERT output "unanswerable" 63% of the time for binary questions and output binary answers for 10% of the unanswerable questions. We would like to identify the reasons behind such confusion between different question categories and improve upon it. We also noticed that the average question lengths for unanswerable questions are about twice as much as binary and number questions, indicating that the workers tend to label "unanswerable" on long questions and the models also perform worse on this type of questions. Therefore, this is also a direction for future improvement.

4.3.2 Image Analysis

We performed image error analysis on vizwiz visual question analysis validation dataset for baseline LSTM+CNN model (Kazemi and Elqursh, 2017). We joined the vizwiz image quality issues dataset (Chiu et al., 2020) with our predictions from LSTM+CNN model to classify input images into 6 flaw categories. Vizwiz image quality issues dataset (Chiu et al., 2020) is annotated with number of votes, out of five crowd workers, for quality flaws. We classified an image as one of the flaw types if at least one crowd worker votes for it. The flaw categories are defined as following: Blur(BLR), Framing(FRM), Dark(DRK), Bright(BRT), Obscured(OBS), Rotation(ROT) and No Flaws(NON). We further calculated accuracy and average edit distance for 3 different question types in each of the image flaw categories: binary(yes/no), number, and unanswerable. See Table 3 for the result.

Based on our analysis, Framing(FRM), Blur(BLR), and Rotation(ROT) are the three most common types of flaws, consisting of 79.28%, 64.24%, and 30.63% of total images. Among all 6 flaw types, Obscured(OBS) performs best with 57.19% overall accuracy, while Rotation(ROT) and Framing(FRM) perform worst with 50.42% and 50.67% accuracy, respectively. We also broke down flaw types into different question types and

Image Quality Issues		Accuracy				Avg Edit Distance			
	% of images	binary	number	unanswerable	total	binary	number	unanswerable	total
BLR	62.24%	68.52%	30.95%	82.21%	51.46%	6.66	8.16	5.87	8.29
FRM	**79.28%**	67.42%	32.77%	82.49%	50.67%	6.86	7.88	6.13	8.67
DRK	19.77%	70.18%	46.15%	80.47%	54.49%	6.26	6.82	6.13	8.13
BRT	18.73%	72.99%	30.00%	86.76%	53.03%	5.97	9.74	5.78	7.86
OBS	13.59%	60.16%	22.22%	82.50%	57.18%	7.07	7.77	5.74	7.26
ROT	30.63%	67.67%	25.49%	81.70%	50.42%	7.54	8.35	6.25	8.65
NON	70.66%	65.44%	26.44%	84.05%	46.82%	6.53	8.36	6.24	9.15
Overall	-	**66.42%**	**30.05%**	**83.02%**	**48.97%**	**6.67**	**8.07**	**6.13**	**8.73**

Table 3: Performance analysis of different image quality issue types on LSTM+CNN model. The quality issue categories are provided by vizwiz image quality issues dataset: Blur(BLR), Framing(FRM), Dark(DRK), Bright(BRT), Obscured(OBS), Rotation(ROT) and No Flaws(NON). In each of the image flaw category, we calculate accuracy and average edit distance for 3 different answer types: binary(yes/no), number and unanswerable.

investigated model performance on each question type. All flaw types have similar performances on unanswerable questions. Obscured(OBS) performs worst on "number" and "binary" questions, producing 22.22% and 60.16% accuracy, respectively. Rotation(ROT) also performs badly on "number" and "binary" questions, carrying out 25.49% and 67.67% accuracy. See Table 3 for details. It's hard to improve performance on FRM or OBS images (large portions of the image are useless), but there are several improvement we can do on ROT images: 1. Use rotational invariance image feature extraction methods, such as CyCNN (Kim et al., 2020). 2. Use data augmentation methods in training to achieve rotational invariance.

It is also interesting to note that No Flaw(NON) image categories indeed achieve 46.82% overall accuracy, which is much worse than flaw image categories. However, we also noticed that NON image categories consist of the lowest unanswerable questions (See Figure 8 for details), potentially leading to the worst performance of NON images. This is also indicated that LSTM+CNN model performs relatively well on unanswerable questions compared to answerable questions. In order to improve the overall model performance, we should mainly focus on the model performance on answerable questions.

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