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MRDQA: A Deep Multimodal Requirement Document Quality Analyzer

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Abstract— In the field of requirement document quality assessment, existing methods mainly focused on textual patterns of requirements. Actually, the cognitive process that experts read and qualitatively measure a requirement document is from outward appearance to inner essence. Inspired by this intuition, this paper proposed a Multimodal Requirement Document Quality Analyzer (MRDQA), a neural model which combines the textual content with the visual rendering of requirement documents for quality assessing. MRDQA can capture implicit quality indicators which do not exist in requirement text, such as tables, diagrams, and visual layout. We evaluated MRDQA on the requirement documents collected from ZTE and achieved 81.3% accuracy in classifying their quality into three levels (high, medium, and low). We have successfully applied MRDQA as a pre-filter in ZTE's requirement review system. It identifies low and medium quality requirements, thereby allows review experts to focus only on high-quality requirements. With this mechanism, the workload can be greatly reduced and the requirement review process can be accelerated.

Index Terms—Requirement Document, Quality Assessment, Visual Rendering, Deep Learning

I. INTRODUCTION

In requirements engineering, it is important to control the quality of requirements from the very beginning of the software development process. However, manual review of requirement documents is laborious and time-consuming. To address this challenge, some tools that can automatically assess the quality of requirements have been proposed, e.g. QuARS [1]. However, existing methods mainly focus on textual content [2]. Up to now, little attention has been paid to the visual information of requirement documents. When an expert reads a requirement document, the first thing that the expert notice is the visual layout appearance, which not only reflects the patterns of diagrams, tables, and text distribution but also indicates the level of organization of requirement content. Inspired by this cognitive process, we proposed MRDQA, a requirement quality classifier that classifies requirement documents into three levels (high, medium, and low). We evaluated MRDQA on a real-world dataset and achieved an encouraging result.

II. THE DESIGN OF MRDQA

Fig. 1 demonstrates the architecture of MRDQA, which consists of the visual cognition subnetwork, the textual characteristics subnetwork, and the concatenation layer.

A. The Visual Cognition Subnetwork

Convolutional Neural Network (CNN) is used to characterize the visual information of requirement documents based on their screenshots. To capture features at different scales, we parallelly connect the EfficientNet-B2 [3] with the EfficientNet-B3 as the backbone of the visual cognition subnetwork. Then, a Singular Value Decomposition (SVD) [4] layer is adopted to capture the most distinguishing features as the output of this subnetwork.

B. The Textual Characteristics Subnetwork

The textual characteristics subnetwork captures three types of features from requirement documents, including completeness features, element statistics (e.g. the number of images), and some metrics (e.g. the number of upvotes) about the requirement web pages. To allow the interactions between different types of feature values (boolean and scalar), we project them into the same feature space through an embedding layer and apply multi-head self-attention layers [5] to learn high-order combination features as the output vector of this subnetwork.

C. The Concatenation Layer

We concatenate the output vectors of the two subnetworks, apply a dense layer and a softmax layer to get a probability distribution of three categories. The corresponding category with the maximum probability is taken as the predicted result.

III. EXPERIMENTS

A. Dataset Construction

We constructed a requirement quality classification dataset[1] with three quality levels. We invited seven requirement experts of ZTE to perform the dataset annotating and finally got 628 real-world requirement document samples (246 high, 205 medium, and 177 low). We randomly select 128 samples as a test set and enlarge the remaining 500 samples by six times with image data augmentation techniques for training and validating.

[1]Due to the company policy, it is inconvenient to open this dataset.

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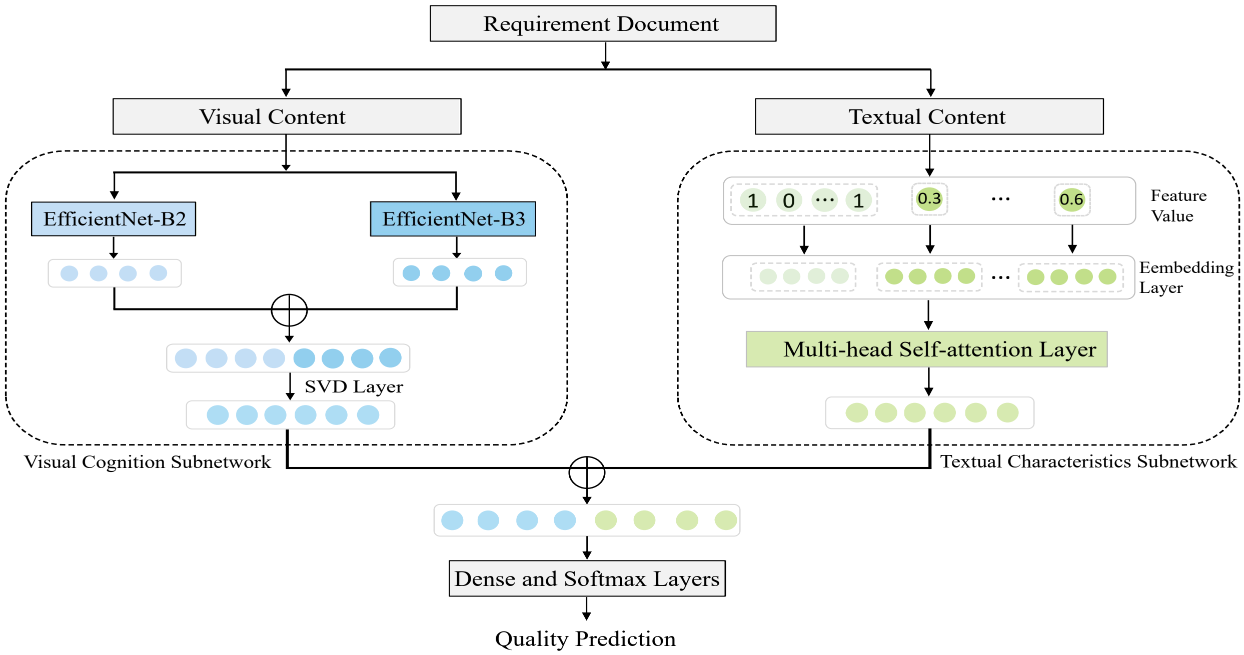

Fig. 1. The Architecture of MRDQA .

TABLE I
PRECISION ("P"), RECALL ("R"), AND ACCURACY ("A") OF MRDQA AND ITS VARIANTS ACROSS THREE LEVELS.

Quality	Metrics	MRDQA-T	MRDQA-V	MRDQA
High	P	71.1%	80.0%	**85.1%**
	R	64.0%	72.0%	**80.0%**
Medium	P	58.1%	60.4%	**72.1%**
	R	59.5%	69.0%	**73.8%**
Low	P	65.0%	80.0%	**86.8%**
	R	72.0%	77.8%	**91.7%**
All	A	64.8%	72.7%	**81.3%**

B. EVALUATION

We evaluate MRDQA on the above-mentioned dataset. To explore the impact of visual and textual information on quality assessment, we construct MRDQA-V based on MARDQA with only enabling the visual cognition subnetwork and MRDQA-T with only enabling the textual characteristics subnetwork. Table I shows that MRDQA achieved 81.3% accuracy, which is higher than that of MRDQA-V and MRDQA-T. This indicates the visual information is effective and can complement textual information to get better results. Besides, the recall and precision for the low-quality requirement documents achieved 91.7% and 86.8% respectively, thus enabling most of the low-quality requirement documents can be identified.

IV. CONCLUSION

This paper proposed MRDQA, a novel model which assesses the quality of requirement documents by characterizing the visual rendering and textual content, and achieved 81.3% accuracy on an industrial dataset. MRDQA can speed up the requirement document review process and save labor costs. For future work, we will focus on extracting more textual features(e.g. various requirement smells) and expanding the dataset. More details are described in the supplementary material[2].

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[2]https://github.com/caojicheng/RE2021-MRDQA