New Vietnamese Corpus for Machine Reading Comprehension of Health News Articles

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Abstract

Although over 95 million people in the world speak the Vietnamese language, there are not any large and qualified datasets for automatic reading comprehension. In addition, machine reading comprehension for the health domain offers great potential for practical applications; however, there is still very little machine reading comprehension research in this domain. In this study, we present ViNewsQA as a new corpus for the low-resource Vietnamese language to evaluate models of machine reading comprehension. The corpus comprises 10,138 human-generated question–answer pairs. Crowdworkers created the questions and answers based on a set of over 2,030 online Vietnamese news articles from the VnExpress news website, where the answers comprised spans extracted from the corresponding articles. In particular, we developed a process of creating a corpus for the Vietnamese language. Comprehensive evaluations demonstrated that our corpus requires abilities beyond simple reasoning such as word matching, as well as demanding difficult reasoning similar to inferences based on single-or-multiple-sentence information. We conducted experiments using state-of-the-art methods for machine reading comprehension to obtain the first baseline performance measures, which will be compared with further models’ performances. We measured human performance based on the corpus and compared it with several strong neural models. Our experiments showed that the best model was BERT, which

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achieved an exact match score of 57.57% and F1-score of 76.90% on our corpus. The significant difference between humans and the best model (F1-score of 15.93%) on the test set of our corpus indicates that improvements in ViNewsQA can be explored in future research. Our corpus is freely available on our website\textsuperscript{1} in order to encourage the research community to make these improvements.

\textit{Keywords:} Span-based Machine Reading Comprehension, Question Answering, Vietnamese

1. Introduction

Recently, question answering (QA) systems have achieved considerable success in a range of benchmark corpora due to the improved development of neural network-based QA (Chen et al., 2017; Wang et al., 2018; Gupta et al., 2019). These QA systems have two main components, where the first component for information retrieval selects text passages that appear relevant to questions from the corpus, and the second component for machine reading comprehension (MRC) extracts answers that are then returned to the user. MRC is a natural language understanding task that requires computers to understand human languages and answer questions by reading a document or an article. In order to evaluate MRC models, standard resources comprising question-answer pairs based on documents have to be collected and annotated in terms of their linguistic features by humans. Therefore, creating a benchmark corpus is vital for human language processing research, especially for low-resource languages such as Vietnamese.

In recent years, researchers have developed many MRC corpora and models in popular languages such as English and Chinese. The best-known examples of gold standard MRC resources for English are span-extraction MRC corpora (Rajpurkar et al., 2016, 2018; Trischler et al., 2016), cloze-style MRC corpora (Hermann et al., 2015; Hill et al., 2015; Cui et al., 2016), reading comprehension with multiple-choice (Richardson et al., 2013; Lai et al., 2017), and conversation-based reading comprehension (Reddy et al., 2019; Sun et al., 2019). Examples of the resources available for other languages include the Chinese corpus for the span-extraction MRC (Cui et al., 2019), traditional Chinese corpus of MRC (Shao et al., 2018), the user-query-log-based

\textsuperscript{1}\url{https://sites.google.com/uit.edu.vn/uit-nlp/datasets-projects}
corpus DuReader (He et al., 2018), and the Korean MRC corpus (Lim et al., 2019). In addition to development of the reading comprehension corpora, various significant neural network-based approaches have been proposed and made a significant advancement in this research field, such as Match-LSTM (Wang and Jiang, 2016), BiDAF (Seo et al., 2016), R-Net (Wang et al., 2017), DrQA (Chen et al., 2017), FusionNet (Huang et al., 2017), FastQA (Weissenborn et al., 2017), QANet (Yu et al., 2018), and S3-NET (Park et al., 2020). Pre-trained language models such as BERT (Devlin et al., 2019) and XLM-R (Conneau et al., 2019) have recently become extremely popular and achieved state-of-the-art results in MRC tasks.

Although researchers have studied several works on the Vietnamese language, such as parsing (Nguyen et al., 2009b, 2014b; Nguyen and Nguyen, 2016; Nguyen et al., 2018a), part-of-speech (Nguyen et al., 2014a; Bach et al., 2018), named entity recognition (Thao et al., 2008; Nguyen et al., 2016, 2019), sentiment analysis (Nguyen et al., 2018b,c; Dang et al., 2018), and question answering (Nguyen et al., 2009a; Nguyen and Le, 2016; Le and Bui, 2018), there is only one corpus for MRC (Nguyen et al., 2020). This corpus comprises of 2,783 multiple-choice questions and answers based on a set of 417 Vietnamese texts used for teaching reading comprehension to 1st to 5th graders. However, this corpus is relatively small and it is not suitable for evaluating deep neural network models for MRC in the Vietnamese language. In addition, machine comprehension for health domain has few studies so far, although it could be implemented into various potential for practical applications such as chatbot and virtual assistant in health-care service. Thus, we aimed to build a new large Vietnamese corpus based on online news articles in the health domain for assessing MRC.

The current approaches based on deep neural networks have surpassed performance of humans with the SQuAD corpus (Rajpurkar et al., 2016) and the NewsQA corpus (Trischler et al., 2016), but it is not clear these state-of-the-art models will obtain similar performance with corpora in different languages. Thus, to further enhance the development of the MRC, we developed a new span-extraction corpus for Vietnamese MRC. Figure 1 shows several examples from our proposed corpus. Our study makes the following three main contributions.

• First, we created a benchmark corpus for evaluating Vietnamese MRC (ViNewsQA) comprising 10,138 human-created question-answer pairs based on 2,030 online news articles in the health domain. The corpus
is available freely for Vietnamese language processing research and also for the cross-lingual studies together with other similar corpora such as SQuAD, CMRC, and KorQuAD.

- We analyzed the corpus in terms of different linguistic features, including three types of length (question, answer, and article) and two content types (question and reasoning), thereby providing insights into the corpus that may facilitate future models. The question and reasoning types were annotated by humans.

- Finally, we developed a framework for Vietnamese MRC and conducted the first experiments based on state-of-the-art MRC models on the ViNewsQA corpus. We also compared their performances with humans based on different linguistic features to obtain insights into Vietnamese span-extraction MRC using different methods.
Reading text: Nghiên cứu cho thấy resveratrol trong rượu vang đỏ có khả năng làm giảm huyết áp, khi thí nghiệm trên chuột. Resveratrol là một hợp chất trong vỏ nho có khả năng chống oxy hóa, chống nấm mốc và ký sinh trùng. Trên Circulation, các nhà khoa học từ King’s College London (Anh) công bố kết quả thí nghiệm tìm ra sự liên quan giữa chuột và resveratrol. Cụ thể, resveratrol tác động đến huyết áp của những con chuột này, làm giảm huyết áp của chúng.

(English translation: The study showed that resveratrol in red wine could reduce blood pressure when tested in mice. Resveratrol is a compound found in grape skin that has antioxidant, anti-mold, and anti-parasitic properties. Scientists from King’s College London (UK) published experimental results in Circulation regarding a link between mice and resveratrol. Specifically, resveratrol lowered the blood pressure of these mice.)

Question 1: Chất bột trong vỏ nho có tác dụng gì?
(English translation: What is the substance in grape skin for?)

Answer 1: có khả năng chống oxy hóa, chống nấm mốc và ký sinh trùng.
(English translation: has antioxidant, anti-mold, and anti-parasitic properties.)

Question 2: Các nhà khoa học từ trường King’s tìm ra phát hiện gì về loại chuột và resveratrol?
(English translation: What did scientists from King’s University discover about mice and resveratrol?)

Answer 2: resveratrol tác động đến huyết áp của những con chuột này, làm giảm huyết áp của chúng.
(English translation: resveratrol lowered the blood pressure of these mice.)

Fig. 1. Several examples from our proposed corpus (ViNewsQA). The English translations are also provided for comparison.

The remainder of this paper is structured as follows. In Section 2, we review the existing corpora and models. In Section 3, we explain the creation of our corpus. The analysis of our corpus is described in Section 4. In Section 5, we present our experimental evaluation and analysis of the results based on the corpus. Finally, we give our conclusions and suggestions for future research in Section 6.

2. Related Work

2.1. Related Corpora

In this study, we constructed an extractive-based MRC corpus in the health domain for the Vietnamese language. Therefore, we review the corpora related to the extractive MRC and the health domain. ViNewsQA
is similar to various recent span-extraction reading comprehension corpora, such as SQuAD (Rajpurkar et al., 2016), NewsQA (Trischler et al., 2016), CMRC (Cui et al., 2019), and KorQuAD (Lim et al., 2019). In particular, CliCR (Šuster and Daelemans, 2018), MedQA (Zhang et al., 2018) are two first MRC datasets in the health domain created in 2018. We summarize the key characteristics of these corpora as follows.

**SQuAD** is one of the best-known English corpora for the extractive MRC and it has facilitated the development of many machine learning models. In 2016, Rajpurkar et al. (2016) proposed SQuAD v1.1 comprising 536 Wikipedia articles with 107,785 human-generated question and answer pairs. SQuAD v2.0 (Rajpurkar et al., 2018) was based on SQuAD v1.1 but it includes over 50,000 unanswerable questions created adversarially using the crowd-worker method according to the original questions.

**NewsQA** is another English corpus proposed by Trischler et al. (2016), which comprises 119,633 question–answer pairs generated by crowd-workers based on 12,744 articles from the CNN news. This corpus is similar to SQuAD because the answer to each question is a text segment of arbitrary length in the corresponding news article.

**CMRC** (Cui et al., 2019) is a span-extraction corpus for Chinese MRC, which was introduced in the Second Evaluation Workshop on Chinese Machine Reading Comprehension in 2018. This corpus contains approximately 20,000 human-annotated questions on Wikipedia articles. This competition attracted many participants to conduct numerous experiments on this corpus.

**KorQuAD** (Lim et al., 2019) is a Korean corpus for span-based MRC, comprising over 70,000 human-generated question-answer pairs based on Korean Wikipedia articles. The data collected and the properties of the data are similar to those in the English standard corpus SQuAD.

**CliCR** (Šuster and Daelemans, 2018) is a medical-domain corpus comprising around 100,000 gap-filling queries based on clinical case reports, while MedQA (Zhang et al., 2018) collected answer real-world multiple-choice questions with large-scale reading comprehension. These corpora required world and background domain knowledge in the study of the MRC models.

Before the present study, a Vietnamese corpus was not available for the span-based MRC research in the health domain. The corpora mentioned above are the benchmark corpora used for the MRC tasks and each can be used to organize a challenging task, thereby encouraging researchers to ex-
plore the machine-learning models on these corpora. Therefore, our primary motivation was to build a Vietnamese corpus in the health domain for MRC tasks.

2.2. Related Methodologies

To the best of our knowledge, many studies have investigated MRC methodologies and the two main types of methods for MRC are rule-based and machine-learning-based.

**Rule-based Approaches.** Sliding window (SW) is a rule-based approach developed by Richardson et al. (2013). This approach matches a set of words built from a question and one of its answer candidates with a given reading text, before calculating the matching score using TF-IDF for each answer candidate. Experiments have been conducted with this simple model on many different corpora as first baseline models, such as MCTest (Richardson et al., 2013), SQuAD (Rajpurkar et al., 2016), DREAM (Sun et al., 2019), and ViMMRC (Nguyen et al., 2020).

**Machine-Learning-Based Approaches.** In addition to the rule-based models, machine-learning-based models have interesting features. In particular, Rajpurkar et al. (2016) introduced a logistic regression model with a range of different linguistic features. However, deep learning models on this problem have obtained outstanding results in recent years. The corpora mentioned in Sub-section 2.1 have been studied in the development and evaluation of various deep learning models in the field of natural language processing, such as Match-LSTM (Wang and Jiang, 2016), BiDAF (Seo et al., 2016), R-Net (Wang et al., 2017), DrQA (Chen et al., 2017), FusionNet (Huang et al., 2017), FastQA (Weissenborn et al., 2017), QANet (Yu et al., 2018), and S3-NET (Park et al., 2020). Recently, (Devlin et al., 2019) and (Conneau et al., 2019) introduced BERT and XLM-R, respectively, as powerful models trained on multiple languages and they obtained state-of-the-art performance with MRC corpora.

In this study, we selected three popular machine-learning methods comprising DrQA, QANet, and BERT, for our MRC and attempted to analyze the experimental results in terms of different linguistic features to obtain first insights into Vietnamese MRC in health domain.
3. Corpus Creation

![Diagram of corpus creation process]

Fig. 2. The process of the Vietnamese MRC corpus creation.

In the following, we explain the process followed to create the Vietnamese MRC corpus, as shown in Figure 2. We constructed our corpus in five different phases comprising worker recruitment, article collection, question and answer sourcing, validation, and collecting additional answers. We describe these phases in detail as follows.

- **Worker recruitment**: We hired workers to build our corpus according to a rigorous process in the following three different stages: (1) Undergraduate students applied to become workers to create the data. (2) The students selected had good at general knowledge and passed our reading comprehension test. (3) In order to become official workers, the selected students were carefully trained based on 500 questions and the data they created was cross-checked to detect common mistakes that can be avoided when creating questions–answer pairs.

- **Reading text collection**: We collected 2,030 news articles related to the health topics from the online newspaper VnExpress⁴. All images,

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⁴https://vnexpress.net/
figures, and tables are eliminated from these articles, and deleted reading text units shorter than 300 characters or those containing many special characters and symbols.

- **Question and answer creation**: The workers read each reading text until it was understood, and they then formulated questions and gave the corresponding answers in the reading text. During the question and answer creation process, the workers conformed to the following rules. (1) Workers were required to ask at least three questions per the reading text. (2) Workers were encouraged to ask questions in their own words and vocabulary. (3) The answers comprised spans in the reading text that satisfied the requirements of our task. (4) Diversity were encouraged in terms of questions, answers, and reasoning.

- **Validation**: Crowd-sourcing is a powerful method for creating a corpus, but errors may occur when creating questions and answers. Thus, in order to obtain a corpus with the highest possible quality, we applied a validation process to mitigate some of these issues, where workers verified question-answer pairs to correct any errors (misspelled questions, incorrect answers, and a lack of or excess amount of information in the answers) in our corpus.

- **Collecting additional answers**: In order to estimate the performance of humans and to enhance our evaluations of the development and test sets, we added three more answers for each question and the first answer in the development and test sets was annotated by workers. During this phase, the workers did not know the first answer and they were encouraged to give diverse answers.

4. Corpus analysis

To obtain insights into our corpus, we conducted our corpus analysis based on various linguistic features. We considered length types (question, answer and article), question types, and inference types in our corpus. In particular, we hired workers to manually annotate of all of the question types and inference types in the development set of our corpus.

4.1. Overall statistics

Statistics for the training, development, and test sets in our corpus are presented in Table 1. The number of questions in ViNewsQA is 10,138 from
2,030 online news articles. We divided the articles randomly into a training set (76%), a development set (12%), and a test set (12%). Table 1 shows the number of articles and the average, maximum, and minimum lengths\(^6\) for questions and answers, and the vocabulary size.

Table 1
Overview of the statistics obtained for ViNewsQA.

|                        | Train | Dev  | Test | All   |
|------------------------|-------|------|------|-------|
| Number of articles     | 1,530 | 250  | 250  | 2,030 |
| Number of questions    | 7,641 | 1,248| 1,249| 10,138|
| Minimum article length | 86    | 104  | 91   | 86    |
| Maximum article length | 743   | 700  | 704  | 743   |
| Average article length | 331.7 | 328.5| 317.0| 329.5 |
| Minimum question length| 4     | 4    | 4    | 4     |
| Maximum question length| 35    | 27   | 32   | 35    |
| Average question length| 10.8  | 10.7 | 10.8 | 10.8  |
| Minimum answer length  | 1     | 1    | 1    | 1     |
| Maximum answer length  | 151   | 79   | 53   | 151   |
| Average answer length  | 10.2  | 10.7 | 9.8  | 10.2  |
| Vocabulary size        | 19,333| 7,504| 7,580| 22,394|

4.2. Question length

Statistics for the various question lengths are shown in Table 2. Questions with 6–10 words comprised the highest proportion with 49.60%. Most of the questions in the corpus had lengths from 6 to 15 words, which accounted for over 87% of the corpus. Very short questions (1–5 words) and long questions (>20 words) accounted for a low percentages of 2.61% and 1.21%, respectively.

\(^6\)We used the pyvi library https://pypi.org/project/pyvi/ for word segmentation to calculate the average, maximum and minimum lengths of articles, questions and answers, and the vocabulary size.
Table 2  
Statistics for the question lengths in ViNewsQA.

| Question length | Training set | Development set | Test set | All   |
|-----------------|--------------|-----------------|---------|-------|
| 1-5             | 2.71         | 1.84            | 2.80    | 2.61  |
| 6-10            | **49.35**    | **51.76**       | **48.92** | **49.60** |
| 11-15           | 38.28        | 37.82           | 38.75   | 38.28 |
| 16-20           | 8.39         | 7.61            | 8.41    | 8.30  |
| >20             | 1.27         | 0.96            | 1.12    | 1.21  |

4.3. Answer length

Table 3 shows the distribution of the answer length analysis in our corpus. The largest percentage (37.07%) comprised answers with lengths of 1–5 words. Most of the answers (over 60%) had lengths of 1–10 words. Longer answers (>15 words) comprised a low proportion of our corpus.

Table 3
Statistics of the answer lengths on ViNewsQA.

| Answer length | Training set | Development set | Test set | All   |
|---------------|--------------|-----------------|---------|-------|
| 1-5           | **37.35**    | **34.46**       | **37.95** | **37.07** |
| 6-10          | 24.92        | 25.96           | 26.42   | 25.23 |
| 11-15         | 17.50        | 16.91           | 17.21   | 17.39 |
| 16-20         | 10.33        | 10.58           | 7.69    | 10.03 |
| >20           | 9.91         | 12.10           | 10.73   | 10.28 |

4.4. Article length

The complexity of reading comprehension depends on the length of the article, so we analyzed article lengths in the corpus. Table 4 presents statistics for various article lengths in our corpus. The lengths of most articles ranged from 201 to 600 words, which accounted for over 75%. Based on the length characteristics, we determined whether the length affected the performance of the machine models and humans according to question, answer or article lengths? The results of the analyses are presented in detail in Section 6.
Table 4
Statistics for ViNewsQA according to the article length.

| Article length | Training set | Development set | Test set | All   |
|----------------|--------------|-----------------|----------|-------|
| <201           | 18.1         | 20.00           | 18.80    | 18.42 |
| 201-400        | 53.33        | 51.60           | 58.40    | 53.74 |
| 401-600        | 23.86        | 22.80           | 18.80    | 23.10 |
| >600           | 4.71         | 5.60            | 4.00     | 4.73  |

4.5. Question type

Because Vietnamese has a similar language model to Chinese, types of question in our corpus follow a manner in the CMRC corpus (Cui et al., 2019). Thus, we divided Vietnamese questions into one of seven question types such as Who, What, When, Where, Why, How, and Others. We hire workers for annotating the type of questions on the development set of our corpus. Table 5 presents the distribution of the question types on our corpus. The table show that the question type What accounted for the largest proportion with 53.09%. Compared to the SQuAD dataset, the rate of the What question in our dataset is similar to that in SQuAD (53.60%) (Aniol et al., 2019). Our corpus requires abilities beyond factoid questions that demand intricate knowledge and skills to answer like Why and How questions. In particular, How and Why ranked the second and the third with 16.28% and 11.87%, respectively.
Table 5
Statistics for the question types in the ViNewQA development set.

| Question type | Example | Percentage (%) |
|---------------|---------|----------------|
| Who           | Ai đẻ bị mổ mâu? | 2.49 |
| English translation: | Who is at risk of blood fats? |
| When          | Cả phẫu thuật lịch sử diễn ra vào thời gian nào? | 2.49 |
| English translation: | When did the surgery history take place? |
| Where         | Người đàn ông 32 tuổi được cấp cứu ở đâu? | 2.89 |
| English translation: | Where is the 32-year-old man who was taken to emergency? |
| Why           | Vì sao ung thư đại trực tràng khó phát hiện? | 11.87 |
| English translation: | Why is colorectal cancer difficult to detect? |
| What          | Một trong những cách khiến gan nhiễm mỡ là gì? | 53.09 |
| English translation: | What is one of the ways to induce fatty liver? |
| How           | Bác sĩ mổ tách hai bé như thế nào? | 16.28 |
| English translation: | How did the surgeon separate the two babies? |
| Others        | Tính bột chiếm bao nhiêu trong một khẩu phần ăn? | 10.91 |
| English translation: | How many carbohydrates are there in a meal? |

4.6. Reasoning type
To classify the difficulty of a question, we divided question reasoning into one of two types, comprising non-inference and inference. Non-inference is simple reasoning, including word matching and paraphrasing, whereas inference is complex reasoning, where the answer is inferred from a single sentence or multiple sentences in the reading text. We hired workers to annotated the reasoning types in the development set for our corpus. Table 6 shows the distributions of the question types in our corpus. The ratio of non-inference relative to inference questions was 7:3.
Table 6
Statistics for the reasoning type in the ViNewQA development set.

| Reasoning type | Example                                                                 | Percentage |
|----------------|-------------------------------------------------------------------------|------------|
| Non-inference  | **Reading text:** Theo Boldsky, ging có đặc tính kháng viêm, thúc đẩy giảm cân, cải thiện tiêu hóa và giúp kích hoạt sự trao đổi chất. Cồn chanh cung cấp **vitamin C** giúp loại bỏ chất tái và độc tố ra khỏi cơ thể.  
(English translation: According to Boldsky, ginger has anti-inflammatory properties, promotes weight loss, improves digestion and helps activate metabolism, while lemons provide **vitamin C** that helps eliminate waste and toxins from the body.)  
**Question:** Chanh bổ sung chất gì giúp cơ thể đào thảo độc tố ra ngoài?  
(English translation: What do lemons contain that helps the human body eliminate toxins out?)  
**Answer:** vitamin C | 70.00% |
| Inference      | **Reading text:** Lô thuốc này bị Cục Quản lý Dược kết luận là "không đạt tiêu chuẩn chất lượng mức độ 2"(thuốc không đạt chất lượng trong quá trình lưu thông). Đây là lô thuốc viên nén bao phim Unicet (Cetirizin hydrochlorid) 10 mg, điều trị các bệnh về đường hô hấp, bệnh về da và mắt. Nhà sản xuất thuốc là Công ty Oripharm của Ấn Độ bị yêu cầu, thu hồi và tiêu hủy toàn bộ lô thuốc, đồng thời bị phạt hành chính.  
(English translation: This batch of drugs was assessed by the Drug Administration of Vietnam as "not up to grade 2 quality standard"(drugs that are not suitable for the circulation process). This is a batch of 10 mg Unicet film-coated tablets (cetirizine hydrochloride), which is used to treat respiratory diseases, skin and eye diseases. The drug manufacturer, Oripharm in India, was required to recall, recall and destroy the entire batch of drugs, and it was administratively fined.)  
**Question:** Tại sao Công ty Oripharm của Ấn Độ bị phạt hành chính?  
(English translation: Why was the Oripharm Company in India penalized with administrative fines?)  
**Answer:** thuốc không đạt chất lượng trong quá trình lưu thông (English translation: for providing drugs that are not suitable for circulation) | 30.00% |
5. Methodology

In this section, we explain our Vietnamese MRC framework, as shown in Figure 3. The pre-processing stage before training involved word segmentation, removing extra whitespaces, and updating the answer positions. In addition, we removed punctuation when performing evaluations. We used pre-trained embeddings for word representations, which have proved effective in several tasks in Vietnamese. Three popular extraction-span MRC methods are chosen for the framework: DrQA Reader (Chen et al., 2017), QANet (Yu et al., 2018), and BERT (Devlin et al., 2019), because these methods have achieved state-of-the-art performance in multiple MRC tasks on SQuAD (Devlin et al., 2019), NewsQA (Joshi et al., 2020), and CMRC (Cui et al., 2019). These models are described as follows.

![Figure 3. The Vietnamese MRC framework.](image)

5.1. DrQA Reader

We implemented the simple but effective neural-based model DrQA Reader, which is based on the open-domain QA system called DrQA proposed by Chen et al. (2017) in 2017. This model has achieved good performance with multiple MRC corpora such as SQuAD (Rajpurkar et al., 2016), and CoQA (Reddy et al., 2019). DrQA is known as a simple-reasoning MRC model with multiple layers. In the input layer, the model presents binary features...
to the lexical-unit embedding of each context lexical unit if this lexical unit and its variants appear in the question. In addition, the model extends the lexical-unit embeddings in the input layer with the linguistic features such as POS and NER. We implemented this method into our corpus as the first baseline models to compare with further models.

5.2. QANet

QANet was proposed by Yu et al. (2018) and this model has also obtained good performance with multiple MRC corpora (Rajpurkar et al., 2016; Dua et al., 2019). Figure 4 provides an overview of the MRC system QANet. QANet has a feedforward architecture with convolutions and attention mechanisms for MRC. The model comprises multiple convolutional layers followed by two components: the self-attention and fully connected layer, for both question and reading text encoding, as well as three stacked layers before predicting the final output.

Fig. 4. Overview of the neural-based MRC architecture QANet Yu et al. (2018).

5.3. Bidirectional encoder representations from transformers (BERT)

Devlin et al. (2019) recently proposed BERT, which uses a transformer network to pre-train a language model for extracting contextual word embeddings. This model is one of the best for contextualized representation
learning (Peters et al., 2018; Howard and Ruder, 2018; Radford et al.; Devlin et al., 2019) and it has achieved the state-of-the-art results in multiple reading comprehension tasks. In this study, we used mBERT (Devlin et al., 2019), as a large-scale multilingual language model, which was pre-trained for evaluating our Vietnamese MRC task. Figure 5 shows an overview of the BERT MRC system.

![Figure 5](image)

**Fig. 5.** Overview of the BERT model architecture for MRC Devlin et al. (2019).

6. Experiments

We conducted experiments using state-of-the-art MRC models comprising DrQA Chen et al. (2017), QANet Yu et al. (2018), and BERT Devlin et al. (2019) on our corpus, as described in Section 4.
6.1. Evaluation metrics

Similar to evaluations of English and Chinese corpora (Rajpurkar et al., 2016; Cui et al., 2019), we used two main evaluation metrics comprising exact match (EM) score and F1-score (macro-average) to evaluate performance of humans and machine models with our corpus. In Vietnamese MRC evaluations, punctuations and white spaces are ignored to allow normalization. The two evaluation metrics are described as follows.

- The exact match is the proportion of predicted answers that match exactly with the gold standard answers.

- The F1-score measures the overlap between the predicted answer and the gold standard answer. First, we generated the predicted answer and gold answer as sets of tokens, and then computed their F1-score. Finally, the evaluation system selected the maximum F1-score from all of the gold standard answers for each question, and then averaged them over all of the questions.

6.2. Human performance

In order to measure the performance of humans with the development and test sets for our corpus, we hired three other workers to independently answer questions using the test and development sets, with four answers per question, as described in the phase for collecting additional answers (see Section 3). In contrast to (Rajpurkar et al., 2016), we used a cross-validation methodology to measure the performance of humans in a similar manner to and similar to (Cui et al., 2019). In particular, we considered the first answer as the human prediction and treated the remainder of the answers as ground truths. We obtained four human prediction performance results by iteratively treating the first, second, third, and fourth answers as the human predictions. We calculated the maximum the performance over all of the ground truth answers for each question. Finally, we averaged the four human prediction results as the final human performance result with on our corpus.

6.3. Experimental settings

For the DrQA and QANet experiments, we used the implementations described in the original studies by (Chen et al., 2017) and (Yu et al., 2018), respectively. However, we only used word features for all of the experiments.

18
with DrQA and QANet models. We used the pyvi tool\(^6\) for word segmentation. We employed 1024-dimensional ELMO word embeddings (Xuan et al., 2019) as our pre-trained Vietnamese word embeddings for DrQA. Also, we used the same pre-trained ELMO word embeddings (Xuan et al., 2019) and the W2V-C2V (Xuan et al., 2019) as our pre-trained char embeddings for QANet.

We used the base-cased multilingual BERT and set of parameters as follows: 12 layers, 768 hidden dimensions, and 12 attention heads (in the transformer) with 179M parameters and a vocabulary of about 120k vocabulary. We selected the best hyperparameters by searching a combination of the batch size, learning rate and the number of fine-tuning epochs from the following ranges: learning rate: \(2 \times 10^{-5}, 3 \times 10^{-5}, 5 \times 10^{-5}\); batch size: 4, 8, 16, 32; number of epochs: 2, 3. The best hyperparameters and models were selected based on the performance with the development set in Vietnamese.

### 6.4. Experimental results

Table 7 compares the performance of our models and humans with the development and test sets for our corpus, and these results are also presented in Figure 6. The best machine model (mBERT) significantly outperformed better than the other models (DrQA and QANet), but not as well as humans. The best model achieved EM = 57.57% and F1-score = 76.90% on the test set. In particular, the performances (EM and F1-score) of the best model with the test set was better than that of the baseline model (DrQA), with 14.01% in EM and 8.63% in F1-score, respectively. The best model also performed better compared with the QANet model, where differences of EM = 11.81% and differences of F1-score = 8.52%. The different performance between humans and the best model (15.93% difference in F1-score) with our corpus was significant, thereby indicating that models for ViNewsQA should be improved in future research.

\(^6\)We used the pyvi library https://pypi.org/project/pyvi/ for word segmentation.
Table 7
Performance of various methods and humans with the development and test sets for our corpus.

| Method               | EM (Dev) | EM (Test) | F1 (Dev) | F1 (Test) |
|----------------------|----------|-----------|----------|-----------|
| DrQA (baseline)      | 42.31    | 43.56     | 68.22    | 68.27     |
| QANet                | 48.09    | 45.76     | 71.41    | 68.38     |
| Best Model (mBERT)   | 61.70    | **57.57** | 80.23    | **76.90** |
| Human performance    | 75.28    | 75.10     | 92.70    | 92.83     |

Fig. 6. Performance of various methods and humans with the development (Dev) and test sets for our corpus.
6.5. Result analysis

To obtain more insights into the performance of the deep neural network models and humans with our corpus, we analyzed their performances based on different linguistic features comprising the question length, answer length, article length, question type, and reasoning type. These features are described in Section 4. In all our analyses, we used $\Delta$ to indicate the difference in performance between humans and the model with the development set for our corpus.

6.5.1. Effects of question length

First, we examined how well the reading comprehension models handled questions with different lengths. In particular, we analyzed the performance of the models and humans in terms of the EM and F1-score evaluation metrics with the development set for ViNewsQA. Table 8 and Table 9 show the detailed analysis of performance results with different questions lengths. In general, more accurate results were obtained for short (1-5 words) and long (≥16 words) than average-length (6-15 words) questions on the best model. The difference in performance between humans and the best model decreased as the question length increased.

Table 8
Performance in terms of EM-score according to the question length with the development set for our corpus.

| Question length | DrQA   | QANet  | Best Model | Human  | $\Delta$ |
|-----------------|--------|--------|------------|--------|---------|
| 1-5             | 39.13  | 36.36  | 65.22      | 86.96  | +21.74  |
| 6-10            | 40.09  | 49.60  | 59.91      | 79.41  | +19.50  |
| 11-15           | 41.95  | 45.77  | 61.65      | 79.45  | +17.80  |
| 16-20           | 57.89  | 50.00  | 69.47      | 82.37  | +12.90  |
| ≥20             | 58.33  | 66.67  | 91.67      | 85.40  | -6.27   |
Table 9
Performance in terms of F1-score according to the question length with the development set for our corpus.

| Question length | DrQA   | QANet  | Best Model | Human | ∆      |
|-----------------|--------|--------|------------|-------|--------|
| 1-5             | 65.48  | 68.41  | 78.02      | 93.55 | +15.53 |
| 6-10            | 67.06  | 71.89  | 77.23      | 92.95 | +15.72 |
| 11-15           | 67.95  | 70.05  | 82.25      | 92.74 | +10.49 |
| 16-20           | 77.17  | 74.01  | 88.73      | 93.52 | +4.79  |
| >20             | 73.95  | 84.31  | 99.31      | 96.18 | -3.13  |

6.5.2. Effects of answer length
In order to examine how well the reading comprehension models could predict the answers with different lengths, we analyzed the performances of the machine models and humans in terms of the EM and F1-score. As can be seen from Table 10 and Table 11, our analysis shows the performances obtained with different answer lengths. In general, more accurate results were obtained for the shorter answer than longer answers in the best model. In particular, the best model achieved the highest performance with short answers (1–5 words) and the lowest performance with long answers (>20 words). Thus, the MRC system had more difficulty finding longer answers. The difference in performance between humans and the best model increased as the question length decreased. The experimental results were the opposite of those obtained in the analysis based on the length of the question.

Table 10
Performance in terms of EM-score according to the answer length with the development set for our corpus.

| Answer length | DrQA    | QANet   | Best Model | Human | ∆      |
|---------------|---------|---------|------------|-------|--------|
| 1-5           | 53.77   | 48.18   | 69.34      | 85.46 | +16.12 |
| 6-10          | 51.44   | 46.84   | 62.93      | 78.09 | +15.16 |
| 11-15         | 49.43   | 53.85   | 60.15      | 75.96 | +15.81 |
| 16-20         | 14.45   | 50.29   | 51.45      | 73.12 | +21.67 |
| >20           | 7.10    | 39.66   | 47.10      | 75.81 | +28.71 |
Table 11
Performance in terms of F1-score according to the answer length with the development set for our corpus.

| Answer length | DrQA   | QANet  | Best Model | Human | Δ    |
|---------------|--------|--------|------------|-------|------|
| 1-5           | 70.19  | 66.58  | 82.72      | 94.40 | +11.68 |
| 6-10          | 73.74  | 73.14  | 80.93      | 91.93 | +11.00 |
| 11-15         | 72.35  | 77.58  | 80.39      | 91.88 | +11.49 |
| 16-20         | 63.30  | 74.22  | 76.47      | 91.93 | +15.46 |
| >20           | 47.48  | 68.80  | 72.99      | 92.31 | +19.32 |

6.5.3. Effects of article length

In addition to determining the impacts of the question and answer lengths on the MRC model for the Vietnamese language, we analyzed the performance of the MRC model and humans (using the EM and F1-score) with various article lengths. The detailed results are presented in Table 12 and Table 13. In general, more accurate results were obtained for shorter articles than longer articles. In particular, the best model achieved the best performance with short answers (<201 words) and the worst performance with long articles (>600 words). Thus, the MRC system had difficulty finding the answer for longer articles. The difference in performance between humans and the best model increased as the question length decreased. The experimental results were similar to those obtained in the analysis based on the answer length.

Table 12
Performance in terms of the EM-score according to the article length with the development set for our corpus.

| Article length | DrQA   | QANet  | Best Model | Human | Δ    |
|----------------|--------|--------|------------|-------|------|
| <201           | 47.58  | 48.37  | 62.50      | 80.34 | +17.84 |
| 201-400        | 43.26  | 49.52  | 65.12      | 80.16 | +15.04 |
| 401-600        | 38.25  | 45.35  | 55.44      | 79.04 | +23.60 |
| >600           | 31.43  | 44.62  | 52.86      | 78.57 | +25.71 |
Table 13
Performance in terms of F1-score according to the article length with the development set for our corpus.

| Article length | DrQA    | QANet   | Best Model | Human  | Δ     |
|---------------|---------|---------|------------|--------|-------|
| <201          | 71.88   | 72.66   | 81.51      | 94.08  | +12.57|
| 201-400       | 68.54   | 71.34   | 81.83      | 93.13  | +11.30|
| 401-600       | 66.02   | 70.24   | 76.80      | 91.69  | +24.89|
| >600          | 61.26   | 72.14   | 74.94      | 92.54  | +17.60|

6.5.4. Effects of question type

We also analyzed the performance of the model and humans in terms of the linguistic features based on the question type. Table 10 and Table 11 show the detailed results obtained for different question types. In general, the "how," "why," "what," and "when" questions in our corpus were more difficult because the performance was lower for these questions compared with others. The MRC system more readily extracted the correct answer for "where" question, and the best model achieved EM = 80.56% and F1-score = 90.11% with the development set. The differences in performance between humans and the best models were high for why, how, what, and who questions (with differences in F1-scores over 13%).

Table 14
Performance in terms of EM-score according to the question type with the development set for our corpus.

| Question type | DrQA    | QANet   | Best Model | Human  | Δ     |
|---------------|---------|---------|------------|--------|-------|
| Who           | 32.26   | 32.14   | 67.74      | 87.90  | +20.16|
| When          | 48.39   | 51.61   | 61.29      | 82.26  | +20.97|
| Where         | 44.44   | 41.67   | 80.56      | 90.28  | +9.72 |
| Why           | 39.86   | 42.55   | 52.70      | 78.21  | +25.51|
| What          | 42.45   | 48.04   | 60.73      | 79.46  | +18.73|
| How           | 34.48   | 45.92   | 55.67      | 76.23  | +20.56|
| Others        | 55.88   | 61.03   | 78.68      | 83.64  | +4.96 |
### Table 15
Performance in terms of F1-score according to the question type with the development set for our corpus.

| Question type | DrQA   | QANet  | Best Model | Human | ∆     |
|---------------|--------|--------|------------|-------|-------|
| Who           | 50.81  | 54.17  | 79.87      | 95.35 | +15.48|
| When          | 65.17  | 67.74  | 72.78      | 93.48 | +20.70|
| Where         | 67.58  | 64.92  | 90.11      | 96.67 | +6.56 |
| Why           | 71.4   | 71.54  | 75.83      | 92.46 | +16.63|
| What          | 67.58  | 71.90  | 79.27      | 92.87 | +13.60|
| How           | 66.97  | 68.17  | 79.06      | 92.22 | +13.16|
| Others        | 74.36  | 79.50  | 90.47      | 93.31 | +2.84 |

### 6.5.5. Effects of reasoning type
We examined how well the MRC models could handle answers with different reasoning types. Table 10 and Table 11 show the performance with different reasoning types. In general, more accurate results were obtained for non-inference questions than inference questions. The differences in performance (F1-score) between humans and the best model were significant, with 19.74% for inference questions and 9.71% for non-inference questions.

### Table 16
Performance in terms of EM-score according to the reasoning type with the development set for our corpus.

| Reasoning type | DrQA   | QANet  | Best Model | Human | Δ     |
|---------------|--------|--------|------------|-------|-------|
| Non-inference | 47.65  | 52.65  | 66.44      | 81.21 | +14.77|
| Inference     | 29.87  | 37.25  | 50.67      | 76.67 | +26.00|

### Table 17
Performance in terms of F1-score according to the reasoning type with the development set for our corpus.

| Reasoning type | DrQA   | QANet  | Best Model | Human | Δ     |
|---------------|--------|--------|------------|-------|-------|
| Non-inference | 72.80  | 75.49  | 83.87      | 93.58 | +9.71 |
| Inference     | 57.57  | 61.68  | 71.76      | 91.50 | +19.74|
6.5.6. Effects of training set size

The training data comprised 7,641 questions, which is much lower than the amount of the data used for English and Chinese MRC systems. Thus, we determined whether the small amount of training data might have contributed to the poor performance of the MRC systems based on evaluations.
with training data sets comprising 1499, 2999, 4496, 5992 and 7641 questions. Figure 7 shows the performance (F1) based on the test set of ViNewsQA. The performance of the systems improved as the size of the training data set increased from 1,499 to 7,641 questions. However, the F1-score was almost saturated when the number of questions increased from 5,992 to 7,641 with DrQA and the best model, and the performance of the QANet model differed significantly with various training data sizes. These observations indicate that the best model (BERT) was more effective with a small amount of training data compared with the other two models. In general, increasing the data size may be required to improve the performance of future models for the Vietnamese MRC.

6.6. Error analysis for selected examples

To obtain a better sense of what errors the MRC models were making, motivating us to select and analyze the following questions, where DrQA, QANet, and BERT all predict wrong.

6.6.1. Ambiguous answers

Many spans in the paragraph can become correct answers for a question, so they create ambiguity in the process of predicting correct answers of the machine models. An example is described as follows.

Reading text: Đang điều trị bệnh thalassemia tại Viện Huyết học - Truyền máu Trung ương, chị Lang Thị Ngoan không giấu được vẻ mệt mỏi, xanh xao. ... "Tôi mang nhóm máu O, nhóm máu luôn trong tình trạng thiếu. Nhiều lần, tôi phải chờ đợi vì viện không đủ máu. Bệnh của tôi cứ phải chờ vào cộng đồng hiến máu", Ngoan nói. (English translation: Treating thalassemia at Blood Transfusion Hematology Hospital, Ms. Lang Thi Ngoan could not hide her tiredness and pallor. ... . "I have the O blood type, and the blood type is always in shortage. Many times, I have to wait because the hospital is not enough blood. My illness keeps waiting in the blood donation community," Ngoan said.)

Question: Vì sao chị Ngoan luôn luôn phải chờ đợi người truyền máu? (English translation: Why is Ngoan always waiting for a blood donor?)

Correct answer: Tôi mang nhóm máu O, nhóm máu luôn trong tình trạng thiếu (English translation: I have the O blood type, and the blood type is always in shortage).
DrQA’s answer prediction: vì viện không đủ máu (English translation: because the hospital is not enough blood).

QANet’s answer prediction: viện không đủ máu (English translation: the hospital is not enough blood).

BERT’s answer prediction: vì viện không đủ máu (English translation: because the hospital is not enough blood).

In this example, we found two spans such as "Tôi mang nhóm máu O, nhóm máu luôn trong tình trạng thiếu" and "vì viện không đủ máu" in the paragraph which are candidate answers to the question "Vì sao chị Ngoan luôn luôn phải chờ đợi người truyền máu?". Although the candidate answers that the three MRC systems predict can be accepted as a correct answer, these answers fail with the EM and F1-score evaluation metrics.

6.6.2. Incorrect boundary

The answers predicted by the three machine models are roughly equivalent to the correct answers, even though they lack or excess some words compared with the correct answers. This error is also easily caused by people. These predicted answers have no meaning in the EM evaluation; however, they are calculated into the F1-score evaluation. An example is described as follows.

Reading text: Ngọc cho biết em học hơn 12 giờ mỗi ngày, bao gồm học chính khóa, học thêm ở trung tâm và ôn bài tại nhà. Nhiều lúc em phải uống cà phê để chống lại cơn buồn ngủ mỗi khi học buổi tối. "Hai tháng trước, em luôn cảm thấy mệt mỏi, cân nặng giảm, hay khóc, nhiều lúc muốn chết, bác sĩ chẩn đoán em mắc chứng trầm cảm phải nhập viện", cô gái 18 tuổi kể. (English translation: Ngoc said she studied more than 12 hours a day, including regular classes, extra classes at the center, and studying at home. Sometimes I have to drink coffee to combat the drowsiness at night. "Two months ago, I always felt tired, lost weight, or cry, sometimes wanted to die, the doctor diagnosed me with depression to be hospitalized," the 18-year-old girl said.)

Question: Vào hai tháng trước, tình trạng mà Ngọc gặp phải trước khi được bác sĩ chẩn đoán là mắc chứng trầm cảm là gì? (English translation: Two months ago, what was the condition that Ngoc encountered before being diagnosed with depression by a doctor?)
Correct answer: luôn cảm thấy mệt mỏi, cân nặng giảm, hay khóc, nhiều lúc muốn chết (English translation: always feel tired, lose weight, or cry, sometimes want to die).

DrQA’s answer prediction: mệt mỏi, cân nặng giảm, hay khóc, nhiều lúc muốn chết (English translation: tired, lose weight, or cry, sometimes want to die).

QANet’s answer prediction: em luôn cảm thấy mệt mỏi, cân nặng giảm, hay khóc, nhiều lúc muốn chết (English translation: I always feel tired, lose weight, often cry, sometimes want to die).

BERT’s answer prediction: mệt mỏi, cân nặng giảm, hay khóc, nhiều lúc muốn chết (English translation: tired, lose weight, or cry, sometimes want to die).

In this question, compared with the correct answer, the DrQA answer prediction lacked of the word "luôn"; on the contrary, the predicted answers of the QANet and BERT models had the addition of the word "em" and the punctuation ",", respectively. However, these answers are acceptable as the correct answers.

6.6.3. Incorrect inference

According to the analysis in Sub-section 6.5, the questions inferred based on single-or-multiple-sentence information have lower results than the non-inference questions. We selected an example for this error, as described follows.

Reading text: Ông Kim Jung Soo 40 tuổi làm việc tại Hải Phòng từ năm 2017 đến nay. Ngày giáp Tết, ông bị đột quỵ tại công ty, được đưa đến cấp cứu tại Bệnh viện Việt Tiệp. ...Bác sĩ chẩn đoán bệnh nhân bị đột quỵ não, xuất huyết dưới nhện do vỡ phình động mạch cảnh. Bệnh nhân được các bác sĩ chuyên khoa đột quỵ não, can thiệp mạch, ngoại thần kinh phối hợp cấp cứu, can thiệp đặt nút coil phình mạch. Các bác sĩ khoa Ngoài thần kinh cũng lên phương án sẵn sàng phẫu thuật nếu có hiện tượng phù não tiến triển. (English translation: Mr. Kim Jung Soo, who is 40 years old, has been working in Hai Phong since 2017. On Tet holiday, he suffered a stroke at the company, and was taken to emergency at the Viet Tiep hospital. ... . The doctor diagnosed the patient with a stroke, subarachnoid hemorrhage due
to the carotid aneurysm rupture. The patient was diagnosed with cerebral stroke specialists, emergency neuropsychiatric interventions, and an aneurysm coil intervention. Neurosurgery doctors also plan to be ready for surgery if there is progressive brain swelling.

**Question**: Ông Soo được các bác sĩ khoa Ngoại thần kinh quan tâm và chuẩn bị gì? (English translation: What was the neurosurgery doctor prepared for Mr. Soo?)

**Correct answer**: sẵn sàng phẫu thuật nếu có hiện tượng phù não tiến triển (English translation: Be ready for surgery if there is a progressive brain swelling).

**DrQA’s answer prediction**: đột quỵ não, can thiệp mạch, ngoại thần kinh phối hợp cấp cứu (English translation: Brain stroke, vascular intervention, neurological emergency coordination).

**QANet’s answer prediction**: đột quỵ não, xuất huyết dưới nhện do vỡ phình động mạch cảnh (English translation: Brain stroke, subarachnoid hemorrhage caused by carotid artery rupture).

**BERT’s answer prediction**: phối hợp cấp cứu, can thiệp đặt nút coil phình mạch (English translation: emergency coordination, intervention with putting the aneurysm coil button).

For this question, "Ông Soo" (Mr. Soo), "bác sĩ" (doctor), "ngoại thần kinh" (neurosurgery), and "chuẩn bị" (prepare) are primary keywords to predict its answer. These words appear in many different sentences in the reading text. These words appear in many different sentences in the reading, which affect the prediction for answers to questions of the machine models.

**6.6.4. Lack of world knowledge**

Some questions require knowledge in order to determine the answers. For example, they may use equivalent words or phrases in questions. These words can be technical terms or concepts of a specific field.

**Reading text**: Hiện, Việt Nam có khoảng 400 phòng khám, 36 khoa tạo hình thẩm mỹ tại các bệnh viện và 25 bệnh viện thẩm mỹ. ... Bộ môn tạo hình thẩm mỹ đầu tiên được thành lập trong trường đại học là của trường Y khoa Phạm Ngọc Thạch, TP HCM, giảng dạy về phẫu
thruat tham my nhu cat mi, cang da mat, sua mui... (English translation: Currently, Vietnam has about 400 clinics, 36 aesthetic clinic faculties at hospitals and 25 aesthetic hospitals. .... The first aesthetic department established in the university was of Pham Ngoc Thach Medical School, Ho Chi Minh City, teaching aesthetic surgery such as eyelid surgery, eye tightening, rhinoplasty ...)

**Question:** Co so dao tao nao tai Viet Nam da thanh lap ra bo mon tao hinh tham my dau tiên? (English translation: Which training center in Vietnam has established the first aesthetic department?)

**Correct answer:** truong Y khoa Pham Ngoc Thach, TP HCM (English translation: Pham Ngoc Thach Medical School, Ho Chi Minh City).

**DrQA’s answer prediction:** khoang 400 phong kham (English translation: about 400 clinics).

**QANet’s answer prediction:** cua truong Y khoa Pham Ngoc Thach, TP HCM, giang day ve phau thuat tham my nhu cat mi, cang da mat, sua mui (English translation: of Pham Ngoc Thach Medical School, Ho Chi Minh City, teaching aesthetic surgery such as eyelid surgery, eye tightening, rhinoplasty).

**BERT’s answer prediction:** cua truong Y khoa Pham Ngoc Thach, TP HCM, (English translation: of Pham Ngoc Thach Medical School, Ho Chi Minh City,).

In this question, "co so dao tao", "Viet Nam", "thanh lap", "bo mon", "tao hinh tham my", "dau tien" are primary keywords to predict its answers. "co so dao tao" is a term in education referring to teaching centers, schools or universities. "co so dao tao" does not appear in the reading text. DrQA predicted the answer "khoang 400 phong kham" for this question, since the word "Viet Nam" in the question appears close to the predicted answer in the reading text. In contrast, QANet and BERT’s predicted answers, which include the correct answer, are not the desired answers.

7. Conclusion and future work

In this study, we developed a span-extraction corpus for evaluating MRC in the low-resource language like Vietnamese. Over 10,000 question–answer
pairs were generated by humans based on a set of 2,030 online health news articles in our corpus. Our corpus contained diverse answer types and a significant proportion of questions (30% of ViNewsQA) required some reasoning ability to solve. The corpus is challenging because our evaluation results showed that the difference in performance between humans and the best model was significant (differences of EM = 17.53% and differences of F1-score = 15.93%). Analyses of the experimental results showed that better results were obtained for long questions with more information than short questions, and short answers and short articles yielded better performance in the best model. In addition, our corpus could be released as a data set for cross-lingual studies based on experiments with other similar corpora, such as SQuAD, NewsQA, and CMRC. In the future, we conduct further investigations to solve the questions that require comprehensive reasoning based on multiple sentences in the reading text. We will also enhance the quantity and the quality of our corpus to achieve better performances with deep neural network and transformer models. Moreover, we would like to operate a Vietnamese MRC challenging shared task for researchers to conduct experiments to explore better models with our corpus.

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