Abstract—This paper proposed several transformer-based approaches for Reliable Intelligence Identification on Vietnamese social network sites at VLSP 2020 evaluation campaign. We exploit both of monolingual and multilingual pre-trained models. Besides, we utilize the ensemble method to improve the robustness of different approaches. Our team achieved a score of 0.9378 at ROC-AUC metric in the private test set which is competitive to other participants.

Index Terms—Transformer-based, fake news, Vietnamese

I. INTRODUCTION

With the emerging of social networks sites in the last decade, the information shared on social network sites (SNSs) gaining attention significantly. SNSs provide platforms for users to share their own content, react, or add comments on the content posted by other users. They help strangers to be connected based on their common interests, activities, identities, or professions [1]. However, issues arise as these information tend to be spread in a rapid and free manners. Many contemporary mainstream news outlets has reported and been cautious that these information can be unreliable, and even political institutions around the world have brought up an emphasis to curb the phenomenon [7]. False information can create a dreadful misunderstand of any particular worldwide event. Therefore, the need for detecting unreliable SNSs through any site or platform has gain unprecedented attention. In this paper we offer a contribution in leveraging multiple pre-trained transformer models to validate identifying shared information in Vietnamese SNSs.

II. METHODOLOGY

There are several pre-trained Transformer-based models in Vietnamese language. They divide into two categories: multilingual such as BERT Multilingual [3], XLM-RoBERTa, and monolingual such as PhoBERT [4], vELECTRA [9], vBERT [9]. In this section, we present our approach to fine-tune the above Transformer-based models for reliable intelligence identification task. Our source code is publicly available.

A. Data Pre-processing

We process the text contents in two phases. First, we tokenize the contents using TweetTokenizer from the NLTK toolkit and use the emoji package to translate icons into text strings. Word segmentation is required in some pre-trained models, we use VnCoreNLP [10] to tokenize the input. In the text content, several features can affect model performance. To clarify this, we duplicate the texts into two versions, one is lower-case texts and no newline characters, the other is raw texts.

In the second phase, to fine-tune the Transformer-based models such as BERT Multilingual, viBERT, and viELECTRA, we must insert [CLS] special token and [SEP] special token to the input. The [CLS] is encoded including all representative information of the whole input sentence. Meanwhile, the use of [SEP] token is simply to separate different sentences of an input. In our method, we only need to insert the [SEP] token to the end of every input. Finally, we convert the new input to the sequence of indices with the same length. We will pad the sequences with the [PAD] token if their length is less than the specified length. In PhoBERT and XLM-RoBERTa, instead of [CLS], [SEP], and [PAD], we use <s>, </s>, <pad> respectively.

1https://github.com/heraclex12/VLSP2020-Fake-News-Detection
2https://www.nltk.org/
3https://pypi.org/project/emoji/
B. Models

1) Single Models: We leverage the ability of pre-trained Transformer-based models, which are trained on large-scale datasets by a variety of unsupervised learning methods. In this task, we list some popular models in the Vietnamese language. They divide into two categories following:

- Multilingual: BERT Multilingual employs masked language model and next sentence prediction for pre-training. Meanwhile, XLM-RoBERTa relies on masked language modeling objective and cross-lingual language modeling objective without next sentence pre-training objective. Both models trained on a large-scale dataset with multiple languages.

- Monolingual: viBERT uses the same architecture as BERT Multilingual. However, it just trained on Vietnamese dataset. viELECTRA is released with viBERT. viELECTRA uses a new pre-training task, called replaced token detection. PhoBERT is also masked language model, which trained on 20GB Vietnamese corpus.

We examine the diversity of input lengths for each of the above models including 256-length, 512-length, and multiple 512-length as a long document. Handling long document is inspired by the research in [5], we segment the input into multiple chunks with the length of 512 and feed them into the Transformer-based model to obtain contextual representations. Then we propagate each output through a Bi-LSTM layer to get document embedding. Finally, we perform the final classification in a linear layer.

We stack a linear classifier on the top of output representations. Instead of just using the last hidden layer, based on the result in [3], we concatenate the last four hidden layers as the input of linear classifier, this modification might slightly improve model performance. For more clearly, Figure 1 illustrates the architecture of our model in detail.

2) Ensemble Method: To utilize the robustness of the different Transformer-based models such as viBERT, viELECTRA, PhoBERT. We select three different Transformer-based models with the highest ROC-AUC score in the validation set. Then, we average their label probabilities to get final probabilities.

C. Results

In public test set, all our models trained on lower-case texts. Some models fail in the validation set. Thus, we do not use them for predicting. As can be seen from Table 1, the monolingual models such as viBERT, viELECTRA, and PhoBERT achieve better performance than the multilingual models. The effectiveness of length is also different for each model architecture. Specifically, viBERT with the length of 512 is worse than 256-length. Meanwhile, viELECTRA with the length of 512 significantly outperforms 256-length viELECTRA, about 3.21% improvement. 512-length viELECTRA also overcomes all single models, it achieves the highest score in both public test and private test.

In order to leverage the ability of the ensemble method, we select three best models with different styles including 256-length viBERT, 512-length viELECTRA, and 256-length PhoBERT to average their output probabilities, we refer this as 3-Ensemble model. In addition, we also denote the top six models with 6-Ensemble. This experiment result demonstrates the ensemble method can further boost the performance.

After reviewing the data, arbitrary capitalization makes the text content unprofessional. In private test set, we investigate
TABLE I
THE RESULTS ON THE PUBLIC TEST SET

| Model | Length  | ROC-AUC |
|-------|---------|---------|
| BERTMultilingual | 512 | 83.36 |
| viBERT | multiple 512 | 88.67 |
| viBERT | 256 | 91.44 |
| viBERT | 512 | 90.20 |
| viELECTRA | multiple 512 | 89.35 |
| viELECTRA | 256 | 89.37 |
| PhoBERT | 512 | 92.58 |
| 3 – Ensemblebase | 256 | 91.79 |
| 6 – Ensemblebase | 256 | 92.20 |

TABLE II
THE RESULTS ON THE PRIVATE TEST SET

| Model | Length  | ROC-AUC |
|-------|---------|---------|
| 3 – Ensemblebase, uncased | 512 | 91.90 |
| viELECTRA, cased | 512 | 93.09 |
| viELECTRA, feature, cased | 512 | 93.78 |
| viELECTRA, uncased | 512 | 91.60 |
| PhoBERT, cased | 256 | 93.01 |
| PhoBERT, uncased | 256 | 91.99 |

the influence of letter case on model performance. viELECTRA with the length of 512 and PhoBERT with the length of 256 achieve the highest score in the public test set, so we decide to train them on the raw texts which remain the upper-case and newline character. The results are described in Table II shows that the cased models significantly improve the uncased models. The ROC-AUC values being 1.49% and 1.02% above the uncased models for viELECTRA and PhoBERT. If only based on text content, it is difficult to identify fake news. In common, the news sources will be an important factor to distinguish reliable information. Because of that, we deliver the username feature into our models. The usernames with high unreliable examples will be penalized, which reduces their output probabilities by a certain value and vice versa. This intuition brings a significant improvement to 512-length cased viELECTRA, from 93.09% to 93.78%.

IV. CONCLUSION AND FUTURE WORK

We conduct extensive experiments to investigate the robustness of multiple Vietnamese pre-trained Transformer-based models to solve the Reliable Intelligence Identification on Vietnamese SNSs problem. Experimental results show that transfer learning method can provide high efficiency in detecting fake news. Along with that is the potential of the ensemble method can be exploited.

Because the nature of news itself can be hard to predict even for humans, in future work, we propose a plan to integrate an external resource checking to validate the source of the news and evaluate this as weights in the models. The news with validated or authorize resources like governments or accredited sites will have higher weights as a piece of real news and vice versa. Besides, we also intend to take advantage of features in images which can provide much evidence for identifying reliable information.

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