Exploring the Feasibility of Detecting Media Frame Indicators in Indonesian News Using Transformer-Based Language Models

Anggrahita Bayu Sasmita
School of Electrical Engineering and Informatics
Bandung Institute of Technology
Bandung, Indonesia
angga.sasmita@itb.ac.id

Ayu Purwarianti
School of Electrical Engineering and Informatics
Bandung Institute of Technology
Bandung, Indonesia
ayu@staff.stei.itb.ac.id

Rinaldi Munir
School of Electrical Engineering and Informatics
Bandung Institute of Technology
Bandung, Indonesia
rinaldi-m@stei.itb.ac.id

***Abstract*—This study explores the feasibility of using transformer-based language models to automate the detection of media frame indicators in Indonesian news articles. Leveraging the general framing framework by Semetko and Valkenburg, the research treats each of the 20 frame indicators as a binary classification task. Using a limited dataset of annotated news articles about two Indonesian public figures, three RoBERTa-based models and one multilingual XLM-R model are fine-tuned and evaluated. The results show varying degrees of classification performance, strongly correlated with the representation of positive samples in the dataset. The study demonstrates the potential of using contextualized language models, previously fine-tuned on IndoNLU and IndoNLI tasks, for identifying latent narrative structures in news text. This approach suggests a shift toward predictive media frame analysis in low-resource settings, with implications for real-time media monitoring and bias detection.**

Keywords—Media Frame Analysis, Natural Language Processing, Transformer Models, RoBERTa, XLM-R, Indonesian Language, Frame Indicator Detection, Text Classification, Low-Resource NLP

I. Introduction

The idea about the framing of news has been proposed initially as a subject of study on how the media outlets behave in presenting the information for their audiences [1]. The study addresses not only printed media, but also some news that had been presented in visual form, of which a particular discussion has been focused on how a series of news presented in either episodic or thematic manner might have influenced the audience's perception on that particular issue [2] The study of media frames has also proposed the idea that a particular issue has to be studied under particular frameworks specific for that issue, while some other frameworks has also been suggested to be relevant for news presentation in general, regardless of the issues being studied [3]. Other than the *episodic-thematic* way of presenting the news, another framework suggests that a particular media outlet has the tendency of focusing on *conflict, economic consequences, human interest, morality,* and *powerlessness* in their writing [1]. These particular focuses are taken as the generic identification of media frames being addressed in this research.

The frames previously mentioned have been suggested to be identifiable through determining a series of narrative characteristics called *framing items* [1]. The study of identifying frames inside a certain news has always been conducted by analyzing the presence of those latent framing items inside that particular news, a process known also as codification. As a news is codified, it is then determined to be showing a tendency of having a particular frame in its writing. A news article could be identified as having more than one frame, for example having the *conflict* and *human interest* frames at the same time. Some further studies have also been conducted to indicate that certain outlets or particular communities show different framing behavior in presenting the news for their audiences [4][5].

The relationship between each framing item and the frame that each of those features represent is measured in a research conducted by Semetko and Valkenburg [6]. In that study, the varimax rotation factor solution is measured for each narrative feature to indicate how much its presence in the text of the news confirms the frame that is used in presenting the news itself. The framing items are derived from the characteristics previously suggested by Neuman [1]. Some adjustments have been made that the frame of *powerlessness* is substituted by the *responsibility* frame using the study of Iyengar [2]. The plausibility of utilizing the narrative aspects to identify particular frame is established from this measurement.

Although the foundation of the identifiable frames through narrative features was initially proposed to define the media behavior in the United States, some attempts of generalizing the framework have also been conducted. Previous studies have explored the feasibility of applying the framework to news topics from socially and culturally diverse regions [5], [7], [8], [9]. The results suggested the possible ubiquity of the framework proposed by Semetko-Valkenburg for its use in identifying media frames.

Due to the necessity for news collection and codification process, media frame analysis has never been a study that can be conducted with immediate results. The availability of frame-codified news that can be converted to a form of dataset for the training process itself is limited as well. The finding on this paper suggests the possibility of providing a computational approach in detecting media frames from several codified news with limited availability. Two preceding studies have been conducted to provide the news collection and codification as the foundation to design the dataset to be utilized in the fine-tuning process [10], [11].

II. Related Works

A. Computational Approaches in Automating Media Frame Identification

Several techniques on identifying media frames using automated means have been studied in its effectiveness, particularly on the classification that utilizes supervised learning methods [12]. The satisfactory result has been shown by a study utilizing the more recently developed transformer-based model [13]. The study suggested that media frame identification could be approached in a similar way as target-dependent sentiment analysis. Such an approach resulted in an indication of the capability of BERT-derived models in solving classification problems for media frame identification.

Some issues have to be addressed in this study for the approach is only relevant for inputs not longer than paragraphs, while the identification of media frames requires the analysis for the entire document. Another issue also needs to be put on consideration for the method proposed by Hamborg involves the frames which are specific for the news topic. The relevance of that approach for the general frame as proposed by Semetko-Valkenburg still needs to be studied. Even so, the suggested method that frame analysis can be approached as parallel to sentiment analysis is taken into consideration, as well as the utilization of simpler transformer-based models such as RoBERTa proposed on the same research.

B. Robustly Optimized BERT Pretraining Approach (RoBERTa)

The approach on the utilization of transformer-based models for natural language understanding was proposed by the design of Bidirectional Encoder Representations from Transformer [14]. The model utilizes the Multi-head Attention mechanism to build representations of the input data before being fed into the neural networks for further processing of inference [15]. Although the original Transformer utilizes the Attention mechanism implemented as both the Decoder and Encoder components, BERT uses the encoder part only and stacks it on several layers. The architecture of the BERT and the breakdowns for its Encoder and Attention mechanism is represented on Fig. 1 as follows.

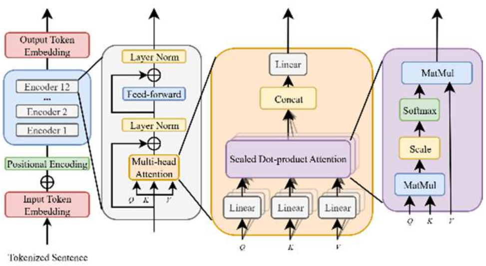

Fig.1. The stacked Encoders that establish BERT and its derivatives

A further modification involves the positional embedding and certain tasks as its pretraining to provide the initial parameters. The first pretrained task is Masked Language Model (MLM), of which a random token in an input sequence is replaced with a masking token, and the model is measured on its cross-entropy loss on predicting the masked token. The sequence is duplicated tenfolds and different ways of masking are provided for each duplicated input for the model to predict. The second pretrained task is Next Sentence Prediction (NSP), of which the model is provided two segments for it to predict that those segments appear consecutively inside a text corpus. It is argued that the NSP loss is necessary to support the downstream tasks of natural language inference.

As BERT's later modification, the design of RoBERTa is focused on primarily the pretraining for the representation while keeping the model architecture itself [16]. Other than the selection of its dataset, an adjustment is made on its masking mechanism for the MLM pretraining. This approach provided a dynamic masking through preprocessing the sequence with randomly replacing the masked token every time that sequence is used to train the model. The second modification in RoBERTa addressed the speculation of the significance of NSP loss in the baseline BERT model. Several training formats have been compared to the original approach, and it has been concluded that the auxiliary NSP loss from segment-pair training is replaceable by utilizing the full token capacity of the encoder (512) for the input. This explanation implies that RoBERTa is fundamentally having the same architecture as BERT, but with its pre-training focused on the MLM task with full utilization of the input token capacity for its training data. The development of RoBERTa also used additional corpora beyond the texts previously pretrained for BERT. The pretraining approach proposed on RoBERTa resulted in overall better performance compared to the baseline BERT. The following Fig. 2 shows the general comparison between BERT and RoBERTa.

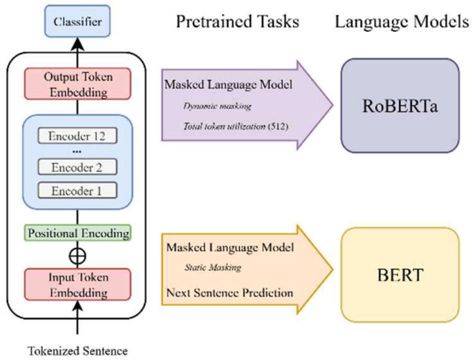

Fig.2. RoBERTa and BERT share the same architecture, but are pretrained through different approaches

C. Adapting the Language Model for Indonesian language

The models being introduced as a RoBERTa derivation for Indonesian language have been constructed using two steps of fine-tunings. The first step involved the usage of OSCAR dataset to fine-tune the baseline RoBERTa and the second step applied the fine-tunings further using the dataset from either IndoNLU benchmark or IndoNLI in separate models. The OSCAR dataset has been proposed to adapt language models in monolingual approach for mid-level availability in resources. The dataset consists of documents collected in five languages, of which for Indonesian itself it has the collection of 140 thousands sentences and 2.3 millions words taken from Common Crawl archive [17]. The Indonesian subcorpora are further parsed into 2.7 millions of tokens in its embedding pipeline.

The initial utilization of OSCAR corpus involves POS-tagging and dependency parsing tasks in conjunction with the UDPipe 2.0 model, which in one case is trained using Indonesian-GSD Treebank [17]. The language models utilized for the contextualized embeddings was ELMO, trained both in Wikipedia and OSCAR corpora for comparison. Results showed the optimum scores for both POS-tagging and dependency parsing tasks, of which dependency parsing was measured in both Unlabeled Attachment and Labeled Attachment scores. That result showed better performance than the UDPipe 2.0 model combined with multilingual BERT (mBERT) in the same experimental environment.

The utilization of OSCAR corpus in pre-training the MLM task for RoBERTa achieved the accuracy value of 62.45% [18]. The model has then been fine-tuned further using both alternative datasets of IndoNLU benchmark and IndoNLI.

D. *Sentiment Classification Fine-tuning on Benchmark Dataset*

IndoNLU was developed to provide an alternative benchmark for natural language understanding similar to GLUE but specified for Indonesian [19]. There are 12 tasks provided for the benchmark that can be further categorized as either classification or sequence labeling. The input also varies between either single sentence or sentence pair. Among those tasks, three of them are relevant for sentiment classification, but two of them are contextualized for very specified domains; only one which has been collected from the general domain, which is the SmSA. The dataset for this task is built from a collection of comments and reviews in Indonesian for varying platforms and annotated as positive, negative, and neutral. The development of SmSA, along with the entire benchmark of IndoNLU was initially provided along with the pre-training of IndoBERT using the Indo4B dataset. The benchmark result for the particular SmSA of IndoBERT (92.72% in macro-F1) was comparable to a multilingual model derived from RoBERTa (92.35% in macro-F1).

A fine-tuning using the dataset SmSA has also been conducted to a derived RoBERTa model pre-trained from OSCAR dataset specifically for Indonesian language [20]. The report shows a comparable result as well for the same task, reaching as high as 92.42% in macro-F1, with 91.02% for the benchmark test set.

E. *Fine-tuning NLI for Indonesian Language*

IndoNLI was developed to provide a similar corpus parallel to the MNLI for Indonesian language [21]. The premise text was taken from Wikipedia and web articles along with the premise news from PUD and GSD of UD 2.5 and IndoSum. The annotation protocol was organized similarly as it had been for MNLI, involving both lay and expert annotators. In total, the IndoNLI corpus provides 17.712 annotated sentence pairs, further categorized into 8368 single-sentences, 1442 double sentences, and 520 paragraphs. The relevant task for the corpus is to classify if the pairs of inputs indicate entailment, contradiction, or have no relation at all. The initial experiment for the IndoNLI involved IndoBERT, multilingual mBERT, and XLM-R, of which in several cases, the XLM-R showed overall best performance.

The modification through fine-tuning the RoBERTa-based language model for Indonesian language through fine-tuning using the IndoNLI dataset proved a comparable performance with the other models experimented as the baselines [22]. The development evaluation achieved 77.06% accuracy, while the test for the lay subset has 74.24% and the expert subset has 61.66% for the same metric.

III. Methods

A. *Task Definition*

The methods conducted for this research involve two parts. The first part is the adjustment for the codification of the news into dataset form. The second part focuses on using the dataset as a downstream classification task using an already fine-tuned language model and analyzing the result. The following explanation details the general method pipeline for this study as depicted on Fig 3.

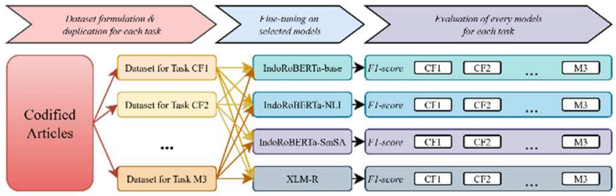

Fig.3. General pipeline for dataset formulation, fine-tuning pretrained models, and evaluation using f1-score on every model for each task

The codified news are taken from the preceding studies of Hanif and Aisy [10], [11]. The studies provided the identification of each framing item on the collected news articles. The topics of the news vary but the subjects are limited to two Indonesian figures, Habib Muhammad Rizieq Shihab (HRS) and Puan Maharani (PM), who had comparable presence in the media between 2018-2021. The selected media outlets for articles of HRS are taken from Tirto and Kumparan, while the news of PM are taken from Okezone and Detik.com. Those outlets presented the articles in Indonesian language with online accessibility at the time this research was conducted.

As this study is focused on identifying the the frame indicators in each news rather than determining the media frames utilized by the outlets for each figure, the identification of the target subjects and the media outlets are ignored. The topic of each news is also omitted from consideration because the study uses the general framing as proposed by Semetko and Valkenburg [6]. The resulting structure of the dataset consists of the text of the news itself and a binary value that classifies the news as having the frame item in it or not. As there are 20 frame indicators for each news, detailed on Table I on the next page, each language model is trained for the similar number of the downstream tasks.

B. *Model Fine-tuning*

The training for the downstream tasks is approached using non-meta learning for few-shot learning, i.e. through using the contextualized language models previously fine-tuned for sentiment classification tasks. The consideration of using sentiment classification is taken from the previous research of Hamborg of approaching the frame identification using target-dependent sentiment classification. Three RoBERTa-based language models are used for comparison in performance, with an addition of XLM-R to represent a multilingual model.

Each model is fine-tuned with the initial parameters in 10 attention layers frozen and the last 2 subjected to adjustment through backpropagation. The learning rate is adjusted at 2e-5 and the epoch is set uniformly in 20. Each model is trained using 80:20 training-test set.

TABLE I. FRAME INDICATORS TO BE IDENTIFIED AS THE DOWNSTREAM CLASSIFICATION TASKS.

Frame Indicator	Task Code
Does the story reflect disagreement between parties-individuals-groups-countries?	CF1
Does one party-individual-group-country reproach another?	CF2
Does the story refer to two sides or to more than two sides of the problem or issue?	CF3
Does the story refer to winners and losers?	CF4
Is there a mention of financial losses or gains now or in the future?	EC1
Is there a mention of the costs/degree of expense involved?	EC2
Is there a reference to economic consequences of pursuing or not pursuing a course of action?	EC3
Does the story provide a human example or "human face" on the issue?	HI1
Does the story employ adjectives or personal vignettes that generate feelings of outrage, empathy-caring, sympathy, or compassion?	HI2
Does the story emphasize how individuals and groups are affected by the issue/problem?	HI3
Does the story go into the private or personal lives of the actors?	HI4
Does the story contain visual information that might generate feelings of outrage, empathy, caring, sympathy, or compassion?	HI5
Does the story suggest that some level of government has the ability to alleviate the problem?	R1
Does the story suggest that some level of the government is responsible for the issue/problem?	R2
Does the story suggest solution(s) to the problem/issue	R3
Does the story suggest that an ind. (or group of people in society) is resp. for the issue-problem?	R4
Does the story suggest the problem requires urgent action?	R5
Does the story contain any moral message?	M1
Does the story make reference to morality, God, and other religious tenets?	M2
Does the story offer specific social prescriptions about how to behave?	M3

The choice of freezing the initial 10 layers is taken due to the utilization of the model parameters from the previous fine tuning using either IndoNLI or SmSA. The frame indicator classification on this study is taken as a further downstream task, of which the model parameters close to the output are to be adjusted in this training process. The choice for learning rate is taken as a lower number than the default value set by Huggingface transformer initiation (5e-5) in order to refine the models more gradually.

The final result is evaluated by the model's macro-f1 score for each task. All models being used for the training are publicly available for download from Huggingface website. The hardware for the GPU-accelerated training uses Nvidia GeForce RTX 2070.

IV. RESULTS AND DISCUSSION

A. Fine-tuning Result

Through this research, an attempt is to be made to indicate the plausibility of identifying media frames through determining the presence of certain narrative features as proposed by the research of Semetko-Valkenburg using supervised learning approach. The data has been initially prepared in the form of codified news, which means that the presence of each narrative aspect has been determined in every collected news. A preliminary research is then conducted to determine whether the narrative aspects are detectable through classification approach, using the more recently developed transformer-based models which have been trained for natural language inference. The detectability is determined by the performance of the model in classifying each of the narrative aspects that present in the news. The high evaluation score that has been achieved through training using available data is implied as the identifiability of the frame indicators through computational means.

The contextualized models that are fine-tuned are downloaded along with their respective tokenizers. This resulted in a different tokenization process that caused the variation between the distribution of training and test set in some models. The distribution of the dataset itself needs to be addressed as the tasks being fine-tuned for the models are not in balanced availability. Moreover, due to the limit of 512 tokens for the input of the encoder, out of 456 collected news, only 295 articles are included for the training process.

B. Model Performance Analysis

Shown on Table II, the F1 scores for each model tasked to classify the respective frame indicators show varying degrees of results. Some models are able to reach the high percentage of the score representing the harmonic means between its precision and sensitivity/recall, while some others fail to even identify the frame indicator in the articles. The failure of the model due to significant lack of positive examples (less than 20%) in the dataset is apparent for the tasks of EC1, EC2, EC3, and CF2. The particular comparison uses the fine-tuning results from the multilingual pre-trained model (XLM-R). On the other hand, the IndoRoBERTa-based models show particularly better result for the tasks with significant lack of positive examples, although the quality still varies.

TABLE II. MODEL EVALUATION COMPARED TO POSITIVE CLASS PROPORTION IN EACH TASK

Tasks	IndoRoBERTa				XLM-R	
	Pos %	Base-F1	+Sm-F1	+NLI-F1	Pos%	F1
CF1	28.47	25.00	33.33	53.33	26.25	30.77
CF2	21.69	15.38	47.06	31.58	18.75	0.00
CF3	48.14	85.25	81.36	82.76	46.25	75.56
CF4	31.53	35.71	46.67	56.25	27.92	71.43
EC1	7.12	40.00	57.14	28.57	6.67	0.00
EC2	4.41	40.00	40.00	40.00	4.17	0.00
EC3	6.78	0.00	33.33	50.00	7.50	0.00
HI1	73.56	86.05	90.91	86.36	73.75	82.67
HI2	63.73	68.57	75.00	69.33	64.17	72.46
HI3	74.24	81.82	87.36	86.67	71.25	72.73
HI4	64.75	88.00	86.49	83.33	63.75	90.00
HI5	33.56	78.05	65.12	68.29	34.58	68.57
R1	48.47	71.43	69.09	72.41	50.83	89.29
R2	43.05	69.39	68.09	63.83	45.00	86.27
R3	71.19	80.00	81.40	81.82	72.92	86.05
R4	56.27	73.24	73.97	71.23	53.33	64.41
R5	60.00	71.43	69.44	63.77	61.25	68.75
M1	49.49	69.09	80.65	75.00	50.42	76.36
M2	25.76	19.05	44.44	42.86	26.25	58.33
M3	75.93	91.95	92.31	90.70	74.17	83.95

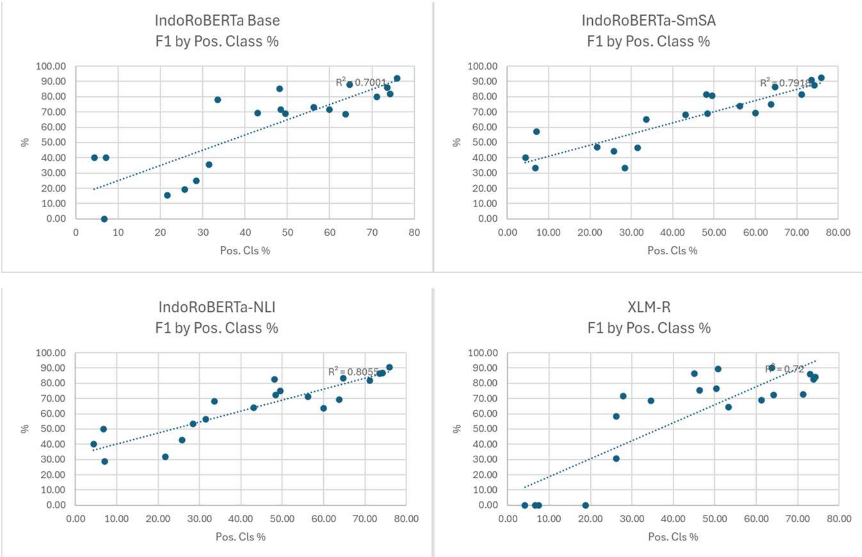

Fig.4. Linear relation between performance of each model and representation proportion of each frame indicator in the dataset.

The difference of the positive examples between IndoRoBERTa-based models and XLM-R also needs to be addressed. The incongruity is caused by the different tokenization methods used for the two variations of the models. The tokenization methods for task CF4 shows the largest gap at 3.61%. The continuation of the research on this subject needs to address the issue of using the tokenization method that would provide congruent positive example proportion for the models being compared.

The figures on Table II also indicate the tendency that the sufficient positive examples are necessary for the fine-tuned models in order to be able to properly detect the frame indicator as the downstream task. The models with positive examples above 45% tend to show better performance, though some exceptions are present. The relationship between the positive examples and the model's performance is determined using trendline analysis comparing the respective positive example percentage and the model performance for each frame indicator detection task.

The graphs presented on Fig. 4 show the R-squared values for each of the trendlines. Those values indicate a common tendency of strong relationship between the model performance and the amount of positive class represented on the dataset. The general trend among the models is that their performance in detecting the frame indicators are positively correlated with the availability of the proportionally represented examples in the dataset. This can be seen as the possibility of detection for frame indicators in news articles in a computational way through utilizing the semantic representation in the document and the language model contextualized for the respective classification tasks.

C. On the Availability of the Data

As per reported, out of 456 collected news, only 295 articles are eligible for training due to the limitation of the input token size of the model. In this preliminary study, the decision to omit the articles that exceed the token size is taken under the reason to retain the semantic integrity of the article in order to be classified more properly. A further preprocessing technique is under a possibility to be suggested, either through automatic summarization for the articles or utilizing other language models that provide the possibility of handling larger token size.

D. Research Implication

The study suggests the plausibility of detecting some general frame indicators as proposed by Semetko-Valkenburg using articles in limited availability. This preliminary study also suggests the identification to be detectable among various topics and different subjects of the articles. Even so, the general lack of positive examples (under 20%) for EC1, EC2, EC3 and CF2 renders the detection of those frame indicators to be unconvincing despite the non-zero macro-f1 in a few models. The zero macro-f1 as shown by the fine-tuned XLM-R further corroborates the need of further analysis on how some models are able to classify the frame indicators with some degree of performance.

The identifiability of general frame indicators through machine learning classification may enable the analysis of media frames to be conducted in a predictive way, in the manner of suggesting the presence of a certain framing in a media that can be provided for the readers. This contrasts with the previous approach on how the media frame analysis has usually been conducted long after the media publicly exposed a certain issue to the readers. The codification process and further statistical analysis are then conducted to determine the tendency of a certain media in presenting the issue through some frames.

This study suggests an alternative way in the form of media frame prediction that may assist audiences to anticipate the certain frame being used by the media outlet to present the issue in an article. However, an ethical consideration needs to be addressed if the language models are to be further developed and applied for wider use. While this could enhance the awareness for the readers on how an issue is presented, a media outlet might risk facing prejudice if it is considered to be too often identified using a certain frame to form its discourse.

V. Conclusion

This research shows the general possibility of performing media frame detection using earlier developed transformer-based language models. The classification task can be developed through separating each of the frame indicators related to the frame aspects and putting the detection of each frame indicator as a task of its own. The experimental result shows varying degrees of performance that correlate strongly with the proportional representation of positive values in the dataset, even with the low number of examples being involved for the training. The result shows the possibility of identifying frame indicators through the semantic aspect of the documents and utilizing the contextualized language model. This also suggests the possibility in further developing models for detecting media frames either through enriching the dataset or using the related frame indicator in a meta-learning approach.

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