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Aspect-Based Sentiment Analysis on Indonesian Presidential Election Using Deep Learning

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Abstrak - Pemilihan presiden tahun 2019 merupakan pemilihan presiden yang menjadi topik hangat selama beberapa waktu sejak tahun 2018. Dalam memprediksi pemenang pemilihan presiden tahun 2019 telah dilakukan penelitian terhadap dataset Analisis sentimen berbasis aspek (ABSA) menggunakan algoritma pembelajaran mesin seperti Support Vector Machine (SVM), Naive Bayes (NB), dan K-Nearest Neighbors (KNN) dan menghasilkan akurasi yang cukup baik. Penelitian ini mengusulkan metode deep learning menggunakan model BERT (Bidirectional Encoder Representation form Transformers) dan RoBERTa (A Robustly Optimized BERT Pretraining Approach). Hasil penelitian ini menunjukkan bahwa model BERT indobenchmark dan RoBERTa base-indonesian single label classification pada fitur target dengan preprocessing menghasilkan akurasi yang terbaik yaitu sebesar 98.02%. Model BERT indolem dan indobenchmark single label classification pada fitur target tanpa preprocessing menghasilkan akurasi yang terbaik yaitu sebesar 98.02%. Model BERT indobenchmark single label classification pada fitur aspek dengan preprocessing menghasilkan akurasi yang terbaik yaitu sebesar 74.26%. Model BERT indolem single label classification pada fitur aspek tanpa preprocessing menghasilkan akurasi yang terbaik yaitu sebesar 74.26%. Model BERT indolem single label classification pada fitur sentiment dengan preprocessing menghasilkan akurasi yang terbaik yaitu sebesar 93.07%. Model BERT indolem single label classification pada fitur sentiment tanpa preprocessing menghasilkan akurasi yang terbaik yaitu sebesar 94.06%. Model BERT indobenchmark multi label classification dengan preprocessing menghasilkan akurasi yang terbaik yaitu sebesar 98.66%. Model BERT indobenchmark multi label classification tanpa preprocessing menghasilkan akurasi yang terbaik yaitu sebesar 98.66%.

Kata Kunci: sentimen analis, deep learning, klasifikasi

***Abstract** - The 2019 presidential election is a presidential election that has been a hot topic for some time since 2018. In predicting the winner of the 2019 presidential election, research has been carried out on Aspect-based Sentiment Analysis (ABSA) datasets using machine learning algorithms such as Support Vector Machine (SVM), Naive Bayes (NB), and K-Nearest Neighbors (KNN) and produces a fairly good accuracy. This study proposes a deep learning method using BERT (Bidirectional Encoder Representation Form Transformers) and RoBERTa (A Robustly Optimized BERT Pretraining Approach) models. The results of this study indicate that the indobenchmark BERT and RoBERTa base-Indonesian single label classification models on target features with preprocessing produce the best accuracy of 98.02%. The indolem BERT model and the indobenchmark single label classification on target features without preprocessing produce the best accuracy of 98.02%. The BERT indobenchmark single label classification model on aspect features with preprocessing produces the best accuracy of 74.26%. The BERT indolem single label classification model on aspect features without preprocessing produces the best accuracy of 74.26%. The BERT indolem single label classification model on the sentiment feature with preprocessing produces the best accuracy of 93.07%. The BERT indolem single label classification model on the sentiment feature without preprocessing produces the best accuracy of 94.06%. The BERT indobenchmark multi label classification model with preprocessing produces the best accuracy of 98.66%. The BERT indobenchmark multi label classification model without preprocessing produces the best accuracy of 98.66%.*

***Keywords**: sentiment analyst, deep learning, classification*

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INTRODUCTION

The 2019 presidential election is a presidential election that has been a hot topic of conversation for some time, and people have even talked about this topic since 2018 on the internet. Social media, such as Twitter and Facebook, have an important role because political parties use social media such as Twitter and Facebook to campaign and advertise their candidates. By using social media, political parties can obtain information that cannot be obtained from the media or traditional voting results, which can be used to predict election results (Suciati et al., 2019).
In predicting the winner of the 2019 Indonesian presidential election, a dataset has been presented using Aspect-Based Sentiment Analysis (ABSA) which focuses on the character of the candidate. ABSA can help organizations become customer-centric so that presidential candidates can listen and understand the voices of their people, evaluate, and learn from people's input and expectations.
Data mining (DM) is a set of techniques and procedures for finding knowledge from various data sources such as data warehouses or relational databases, into an unformatted flat file created from predictive analysis using statistical study techniques to predict or anticipate certainty-based statistical measures. This knowledge can be classified in different rules and patterns that can help users/organizations to analyze collective data and predict decisions (Hamid Mughal, 2018) (Manjarres et al., 2018).
Natural Language Processing (NLP) is also known as the field of computational linguistics, which involves engineering computational models and processes to solve practical problems in understanding human language (Otter et al., 2021). From a scientific perspective, NLP aims to model the cognitive mechanisms underlying human language comprehension and production. From an engineering perspective, NLP is concerned with developing new practical applications to facilitate the interaction between computers and human language.
Sentiment analysis, also known as opinion mining, is a field within NLP that studies the computation of opinions, emotions, and subjectivity contained in text and often in negative, neutral and positive categories. Sentiments are collected, analyzed, and then summarized to produce real-time feedback (Hoang et al., 2019) (Sun et al., 2019).
ABSA is a text mining method that organizes text into targets and aspects and then labels each as a sentiment polarity. This is different from the usual sentiment analysis which only recognizes the overall polarity of the text (Manik et al., 2020). Polarity gives the difference between the number of positive words and the number of negative words in each text divided by the number of sentiment words(Budiharto & Meiliana, 2018).
Machine learning (ML) is a branch of Artificial Intelligence (AI) and is closely related to (and often overlaps with) computational statistics, which also focuses on making predictions using computers. Like DM, ML can also be unsupervised learning and is used to study and define basic behavior profiles for various entities and then use it to find meaningful anomalies (Xin et al., 2018). ML focuses on classification and regression based on known and previously learned features of training data. The engine learns a given pattern based on the data set and generates its own rules. When data is entered into the machine, the machine can recognize the data.
Previous research has conducted on the 2019 presidential election ABSA dataset using machine learning algorithms such as the Support Vector Machine (SVM), Naive Bayes (NB), and K-Nearest Neighbors (KNN) and produced a fairly good accuracy on target class, aspect and sentiment.

RESEARCH METHODOLOGY

1. Research Dataset

The dataset used in this study is the 2019 presidential election ABSA dataset which consists of 2019 instances and 5 features.

	target	aspect	sentiment	id	tweet
0	PRABOWO	LEADERSHIP	POSITIVE	476965496395268096	Prabowo Memang Tegas. Mantap!! @BULLFRONT http...
1	PRABOWO	LEADERSHIP	NEGATIVE	468737132803026944	Sementara Prabowo menvla mencle. Dulu dia bila...
2	PRABOWO-SANDIAGA UNO	OTHER	POSITIVE	1067695201966219265	Pemimpin Agama apaan, cawapres jokowi tuh kiay...
3	JOKOWI	LEADERSHIP	NEGATIVE	1067694193286406144	@CNNIndonesia Karena Pak @jokowi ga tegas cend...
4	JOKOWI-MA'RUF AMIN	EMPATHY	POSITIVE	1067666046478237696	Karen's @jokowi ma'ruf pasangan yang sederhana...
...	...	...	...	...	...
2014	JOKOWI	INTEGRITY	POSITIVE	1028886286830993410	Aku ga mau golput karena aku percaya sama Joko...
2015	MA'RUF AMIN	LEADERSHIP	POSITIVE	1027757907771703296	#cawapres #marufamin figur yang melambangkan #...
2016	PRABOWO-SANDIAGA UNO	LEADERSHIP	POSITIVE	1027595781224587264	Prabowo Sandi uno Diterima Semua Kalangan Nasi...
2017	MA'RUF AMIN	LEADERSHIP	POSITIVE	1027577142132072448	euG ngefans sama Pa Ma'ruf sejak jaman belio d...
2018	PRABOWO	INTEGRITY	POSITIVE	1024779696884482049	Prabowo:\ngak korupsi\ngak nipu\ngak jual aset...

2019 rows × 5 columns

Source: (Said & Manik, 2022)

Figure 1. Research Dataset

Table 1. Attributes of Research Dataset

id	Pengenal
tweet	Collected tweet data
target	Candidates for president and vice president
aspect	Characters of the presidential and vice presidential candidates
sentiment	The sentiment that emerged from the tweet

Source: (Said & Manik, 2022)

The target feature has 6 classes, namely JOKOWI, JOKOWI-MA'RUF AMIN, MA'RUF AMIN, PRABOWO, PRABOWO-SANDIAGA UNO, SANDIAGA UNO. The aspect feature has 5 classes, namely COMPETENCE, EMPATHY, INTEGRITY, LEADERSHIP, OTHER. The sentiment feature has 3 classes, namely POSITIVE, NEGATIVE, NEUTRAL.

Table 2. Class Distribution

Target	Aspect	Sentiment
JOKOWI (787)	INTEGRITY (484)	POSITIVE (1261)
PRABOWO (472)	EMPATHY (407)	NEGATIVE (731)
SANDIAGA UNO (387)	LEADERSHIP (403)	NEUTRAL (27)
PRABOWO-SANDIAGA UNO (202)	COMPETENCE (373)	
MA'RUF AMIN (115)	OTHER (352)	
JOKOWI-MA'RUF AMIN (56)		

Source: (Said & Manik, 2022)

2. Preprocessing

The first preprocessing in this research is data cleaning where the process is to homogenize all text into lowercase letters (lowercase), clean data containing url (http://), tabs and newlines, non ascii characters, punctuation, whitespace, reply. threads, numbers, and delimiters such as commas (,), and periods (.), but do not delete username tokens (@), do not delete emojis, and do not delete hashtag tokens (#) as shown in Figure 2.

	target	aspect	sentiment	id	tweet
0	PRABOWO	LEADERSHIP	POSITIVE	476965496395268096	prabowo memang tegas . mantap !! @bullfront
1	PRABOWO	LEADERSHIP	NEGATIVE	468737132803026944	sementara prabowo menvla mencle . dulu dia bil...
2	PRABOWO-SANDIAGA UNO	OTHER	POSITIVE	1067695201966219265	pemimpin agama apaan , cawapres jokowi tuh kia...
3	JOKOWI	LEADERSHIP	NEGATIVE	1067694193286406144	@cnnindonesia karena pak @jokowi ga tegas cend...
4	JOKOWI-MA'RUF AMIN	EMPATHY	POSITIVE	1067666046478237696	karen ' s @jokowi ma ' ruf pasangan yang seder...
5	JOKOWI	LEADERSHIP	POSITIVE	1067664862786945027	jokowi sangat menginspirasi #pilihjokowi #pili...
6	PRABOWO	INTEGRITY	NEGATIVE	1067663506051231744	@prabowo terlalu mudah percaya dan kurang krit...
7	PRABOWO	OTHER	POSITIVE	1067659392961601537	@prabowo apapun itu sy terus mendukung pak pra...
8	PRABOWO	INTEGRITY	NEGATIVE	1067653182308773888	@chloetowntale @mbahuyok jujur kami kecewa ber...
9	JOKOWI	LEADERSHIP	NEGATIVE	1067648896728330240	saya sangat marah dan kecewa , karena kualitas...

Source: (Said & Manik, 2022)

Figure 2. Data cleaning process

The next step is to do stemming to change all the words in the document into basic words by eliminating all affixes, namely prefixes, suffixes, infixes, and confixes as shown in Figure 3.

	target	aspect	sentiment	id	tweet
0	PRABOWO	LEADERSHIP	POSITIVE	476965496395268096	prabowo memang tegas mantap bullfront
1	PRABOWO	LEADERSHIP	NEGATIVE	468737132803026944	sementara prabowo menvla mencle dulu dia bilan...
2	PRABOWO-SANDIAGA UNO	OTHER	POSITIVE	1067695201966219265	pimpin agama apa cawapres jokowi tuh kiayi kit...
3	JOKOWI	LEADERSHIP	NEGATIVE	1067694193286406144	cnnindonesia karena pak jokowi ga tegas cendru...
4	JOKOWI-MA'RUF AMIN	EMPATHY	POSITIVE	1067666046478237696	karen s jokowi ma ruf pasang yang sederhana na...
5	JOKOWI	LEADERSHIP	POSITIVE	1067664862786945027	jokowi sangat inspirasi pilihjokowi pilihjokow...
6	PRABOWO	INTEGRITY	NEGATIVE	1067663506051231744	prabowo terlalu mudah percaya dan kurang kriti...
7	PRABOWO	OTHER	POSITIVE	1067659392961601537	prabowo apa itu sy terus dukung pak prabowo in...
8	PRABOWO	INTEGRITY	NEGATIVE	1067653182308773888	chloetowntale mbahuyok jujur kami kecewa berat...
9	JOKOWI	LEADERSHIP	NEGATIVE	1067648896728330240	saya sangat marah dan kecewa karena kualitas p...

Source: (Said & Manik, 2022)

Figure 3. *Stemming*

The last step is encoding. Two categorical encoding techniques are used, the first is Label Encoding which is used to convert labels to numeric form by assigning a unique number (starting from 0) to each data class. The second is One Hot Encoding which changes each categorical variable into a new column and each column contains the number "0" or "1" which corresponds to which column the label or category is in. (Waasiu et al., 2021) The use of these two categorical encoding techniques depends on what classification technique will be used when implementing the BERT and RoBERTa models (single label classification or multi label classification).

3. Implementation of BERT and RoBERTa

Before training the dataset, the dataset is adjusted to the input representation that will be received by BERT and RoBERTa. Therefore we need a tokenizer that aims to tokenize sentences and generate appropriate input. Sentences will be processed by the tokenizer to represent the input on BERT and also RoBERTa. In this study, the BERT model used is indolem and indobenchmark, while the RoBERTa model used is robert-base-indonesian.

Each sentence will be broken down into words using a wordpiece and will get the ID of the word. Each word will get a token that has become a system provision. Each sentence will also get a special token at the beginning and end of the sentence. In BERT the tokens used are [CLS] for tokens at the beginning of sentences and [SEP] for tokens at the end of sentences. While in RoBERTa the tokens used are <s> for tokens at the beginning of sentences and </s> for tokens at the end of sentences.

After that, the sentence is adjusted to the maximum length that has been determined using [PAD] on BERT and <pad> on RoBERTa. Because the maximum length specified is 32, both [PAD] and <pad> will be useful to fill in the blanks if the sentence is not up to 32 words. Sentence embedding is given to the sentence to distinguish the first sentence and the second sentence or padding. This stage can be done by giving the number 1 in the first sentence and giving the number 0 in the padding. The BERT tokenizer can find out which is the first sentence and which is the padding by looking at the [SEP] token which functions to separate the two sentences.

Positional embedding is also added for each token to indicate the position of each word in the sentence. This stage is done to find out the position of each word. So even though at the beginning of the sentence there is a word and at the end of the sentence there is also the same word but has a different meaning, it will not treat the token with the same meaning.

```
['[CLS]',
 'cn',
 '##ni',
 '##nd',
 '##onesia',
 'karena',
 'pak',
 'jokowi',
 'ga',
 'tegas',
 'cend',
 '##rung',
 'lemah',
 '[SEP]',
 '[PAD]',
 '[PAD]',
 '[PAD]',
 '[PAD]',
 '[PAD]',
 '[PAD]',
 '[PAD]',
 '[PAD]',
 '[PAD]',
 '[PAD]',
 '[PAD]',
 '[PAD]',
 '[PAD]',
 '[PAD]',
 '[PAD]',
 '[PAD]',
 '[PAD]',
 '[PAD]']
```

```
['[CLS]',
 'cnn',
 '##indonesia',
 'karena',
 'pak',
 'jokowi',
 'ga',
 'tegas',
 'cend',
 '##rung',
 'lemah',
 '[SEP]',
 '[PAD]',
 '[PAD]',
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 '[PAD]',
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 '[PAD]',
 '[PAD]',
 '[PAD]',
 '[PAD]',
 '[PAD]',
 '[PAD]',
 '[PAD]',
 '[PAD]',
 '[PAD]',
 '[PAD]',
 '[PAD]',
 '[PAD]',
 '[PAD]']
```

```
['<s>',
 '@',
 'CN',
 'N',
 'Indonesia',
 'ĠKarena',
 'ĠPak',
 'Ġ@',
 'j',
 'okowi',
 'Ġga',
 'Ġtegas',
 'Ġc',
 'end',
 'rung',
 'Ġlemah',
 '</s>',
 '<pad>',
 '<pad>',
 '<pad>',
 '<pad>',
 '<pad>',
 '<pad>',
 '<pad>',
 '<pad>',
 '<pad>',
 '<pad>',
 '<pad>',
 '<pad>',
 '<pad>',
 '<pad>',
 '<pad>']
```

Source: (Said & Manik, 2022)

Figure 4. The tokenization process using the BERT and RoBERTa models

4. Fine Tuning

This study performs fine tuning using hyperparameters on BERT and RoBBERTa, where the best accuracy results are obtained using hyperparameters as shown in Table 3.

Table 3. Hyperparameters

Fine Tuning on Target Feature	Fine Tuning on Aspect Features	Fine Tuning on Sentiment Features	Fine Tuning on Multilabel Classification
- *Batch Size* : 8 - *Epoch* : 10 - *Optimizer* : *Adam* - *Learning Rate* : 1e-5	- *Batch Size* : 8 - *Epoch* : 10 - *Optimizer* : *Adam* - *Learning Rate* : 1e-5	- *Batch Size* : 24 - *Epoch* : 10 - *Optimizer* : *Adam* - *Learning Rate* : 2e-5	- *Batch Size* : 8 - *Epoch* : 10 - *Optimizer* : *Adam* - *Learning Rate* : 1e-5

Source: (Said & Manik, 2022)

RESULTS AND DISCUSSION

Prior to classification, the dataset is divided into training datasets, validation datasets, and testing datasets. The training dataset is used to train the model. While the validation dataset is used to minimize overfitting. The testing dataset itself is used as a final test to see the accuracy of the network that has been trained with the training dataset.

After the data preprocessing process, fine tuning is carried out on the data using the following hyperparameters:

a. Fine Tuning on target features: Batch Size: 8, Epoch: 10, Optimizer : Adam, Learning Rate: 1e-5
b. Fine Tuning on aspect features: Batch Size: 8, Epoch: 10, Optimizer : Adam, Learning Rate: 1e-5
c. Fine Tuning on sentiment features : Batch Size: 24, Epoch: 10, Optimizer : Adam, Learning Rate: 2e-5
d. Fine Tuning on multi label classification: Batch Size: 8, Epoch: 10, Optimizer : Adam, Learning Rate: 1e-5

test results on these features produce the following accuracy values:

1. Single Label Classification

a. Single Label Classification with Preprocessing

Table 4. Test results on target features

Classification Method	Test Accuracy	Train Accuracy
BERT indolem	97.03 %	98.79 %
BERT indobenchmark	98.02 %	99.28 %
RoBERTa base-indonesian	98.02 %	99.17 %

Source: (Said & Manik, 2022)

Table 5. Test results on aspect features

Classification Method	Test Accuracy	Train Accuracy
BERT indolem	72.28 %	98.9 %
BERT indobenchmark	74.26 %	99.83 %
RoBERTa base-indonesian	65.35 %	99.06 %

Source: (Said & Manik, 2022)

Table 6. Test results on the sentiment feature

Classification Method	Test Accuracy	Train Accuracy
BERT indolem	93.07 %	99.72 %
BERT indobenchmark	90.1 %	99.83 %
RoBERTa base-indonesian	87.13 %	99.61 %

Source: (Said & Manik, 2022)

Table 4 shows that the indobenchmark BERT and the Indonesian-based RoBERTa get the best accuracy on the target feature, which is 98.02%. Table 5 shows that the indobenchmark BERT gets the best accuracy on aspect features, which is 74.26%. Table 6 shows that BERT indolem gets the best accuracy on the sentiment feature, which is 93.07%.

b. Single Label Classification without Preprocessing

Table 7. Test results on target features

Classification Method	Test Accuracy	Train Accuracy
BERT indolem	98.02 %	98.35 %
BERT indobenchmark	98.02 %	99.28 %
RoBERTa base-indonesian	95.05 %	99.06 %

Source: (Said & Manik, 2022)

Table 8. Test results on aspect features

Classification Method	Test Accurac y	Train Accurac y
BERT indolem	74.26 %	97.19 %
BERT indobenchmark	72.28 %	99.83 %
RoBERTa base-indonesian	65.35 %	99.39 %

Source: (Said & Manik, 2022)

Table 9. Test results on the sentiment feature

Classification Method	Test Accuracy	Train Accuracy
BERT indolem	94.06 %	99.83 %
BERT indobenchmark	92.08 %	99.83 %

RoBERTa base-indonesian	82. 18 %	99.78 %	

Source: (Said & Manik, 2022)

Table 7 shows that indolem BERT and BERT get the best accuracy on the target feature, which is 98.02%. Table 8 shows that BERT indolem gets the best accuracy on aspect features, which is 74.26%. Table 9 shows that BERT indolem gets the best accuracy on the sentiment feature, which is 94.06%.

2. Multi Label Classification

Table 10. Test results of multi label classification with preprocessing

Classification Method	Accuracy	F1 Micro	F1 Macro
BERT indolem	89.9 %	97.79 %	95.25 %
BERT indobenchmark	98.66 %	99.5 %	98.47 %
RoBERTa base-indonesian	96.33 %	99.06 %	97.27 %

Source: (Said & Manik, 2022)

Table 11. Multi label classification test results without preprocessing

Classification Method	Accuracy	F1 Micro	F1 Macro
BERT indolem	96.33 %	99.1 %	97.4 %
BERT indobenchmark	98.66 %	99.53 %	98.95 %
RoBERTa base-indonesian	97.23 %	99.18 %	97.26 %

Source: (Said & Manik, 2022)

Table 10 and Table 11 show that the indobenchmark BERT gets the best accuracy in the multilabel classification technique with or without preprocessing.

CONCLUSION

The BERT and RoBERTa models are able to perform target, aspect and sentiment analysis tasks well, both using single label classification and multi label classification. BERT indobenchmark and RoBERTa base-Indonesian single label classification on target features with preprocessing resulted in the best accuracy of 98.02%. BERT indolem and indobenchmark single label classification on target features without preprocessing produce the best accuracy of 98.02%. BERT indobenchmark single label classification on aspect features with preprocessing produces the best accuracy of 74.26%. BERT indolem single label classification on aspect features without preprocessing produces the best accuracy of 74.26%. BERT indolem single label classification on the sentiment feature with preprocessing produces the best accuracy of 93.07%. BERT indolem single label classification on the sentiment feature without preprocessing produces the best accuracy of 94.06%. BERT indobenchmark multi label classification with preprocessing produces the best accuracy of 98.66%. BERT indobenchmark multi label classification without preprocessing produces the best accuracy of 98.66%.

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