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Deep Learning for Multi-Aspect Sentiment Analysis of TikTok App using the RNN-LSTM Method

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Abstract−Applications built expressly for consumers to communicate online are known as social media apps. Social media applications are utilized for enjoyment as well as for interacting. For Android users, applications may be found in the Google Play Store, while for iOS users, they can be found in the Apple App Store. The site offers a collection that is a big resource-rich in thoughts, opinions, and feelings, notably on Google Playstore. Each user's review has an aspect value. Due to a large number of reviews, sentiment analysis is tough. The author proposes to do an Aspect-Based Sentiment Analysis (ABSA) utilizing TikTok app reviews on the Google Play Store in this paper. Currently, there are 65.2 million active users of the Tik Tok program, including 8.5 million users from Indonesia, there are still a few studies that use the TikTok application dataset. In this study, sentiment classification is carried out on each aspect that has been determined, namely, aspects of features, business, and content, the method used is deep learning Recurrent Neural Network with the Long Short-Term Memory (RNN – LSTM) model and the addition of word embedding BERT. The results showed that the classification of sentiment in the business aspect showed the highest score, namely 0.94, the sentiment classification in the aspect received an accuracy of 0.91 while the feature aspect got the lowest accuracy, which was 0.85.

Keywords: Sentiment analysis; Deep learning; LSTM; Multi-aspect; Word embedding

1. INTRODUCTION

A social media application is a computer program that is made specifically to do the tasks of its users in interacting online. In addition to interacting, social applications are also used as entertainment media to have fun and relieve the boredom of users. One of the social media applications is Tiktok with its feature of making short videos between users which makes the Tiktok application popular. Currently, the number of active users of the TikTok application is 65.2 million downloads with 8.5 being users from Indonesia [1]. The TikTok application can be downloaded on Google Playstore for Android users, Google PlayStore provides a review feature to rate the services of an application, movie, ebook, and others. With the review feature, a very large amount of text data is available. The collection of texts is a great resource-rich in opinions, opinions, and sentiments. A large number of reviews makes it difficult to process sentiment analysis. Therefore we need a system that can perform sentiment analysis based on aspects of the review.

Sentiment analysis attracts interest from both research and industry. Aspect-based sentiment analysis is fundamental which aims to infer the polarity of a sentence's sentiment concerning a given aspect. For example, "The application is good, it can make money from advertisements, but many videos are bad." This opinion can be seen that about business is positive while content is negative. In this case, there are several aspects in a comment, aspect-based sentiment analysis is commonly called Aspect-based sentiment analysis (ABSA) [2]

In his research [3] proposed a deep learning model for Aspect-based Sentiment Analysis (ABSA). The study showed good results in the aspect classification using 5,387 data. From the comparison of deep learning methods, the researchers found that the accuracy values in each model were not too different. Attention BiLSTM got the lowest score with an accuracy value of 0.896, and the LSTM model had the best result with an accuracy score of 0.926.In his research.

Word embedding is used to get vector values in the deep learning method from Long Short-Term Memory (LSTM) for sentiment classification. The results showed that the combination of the PLSA + TF ICF 100% + Semantic Similarity method was superior, namely 0.840 in the categorization of the five hotel aspects, and the Word Embedding + LSTM method outperformed the sentiment classification at a value of 0.946 [4]

The Bidirectional GRU and Word Embedding methods are used in sentiment analysis because they have the advantage of being able to include the semantic meaning of words in a text. There are various types of word insertion models, such as the Glove, which focuses on words that appear together. Deep Learning Algorithm requires a scalar or matrix value to process the words. Words are converted to vectors while preserving semantic context. This representation is known as Word Embedding [5].

In the aspect-based sentiment analysis research using LSTM and fuzzy logic, the proposed fuzzy logic and LSTM models were tested on ACPR, AVGR, and CPAP data sets, and customer reviews grouped by geographic location. The proposed model is tested separately according to each country. The proposed model for aspect-based sentiment analysis adopts the ClausIE feature to divide long sentences into small ones, the result is that word embedding is suitable for use for aspect-based analysis. three publicly available data sets with 96.93% accuracy on ACPR, 83.82% accuracy on AVGR, and 90.92% accuracy on the CRAP data set [6].

In J. Wang et all's research in 2018, the Word&Clause-Level ATT model impressively outperformed the LSTM to get the highest accuracy of 0.809 in the restaurant data set and 0.816 in the laptop data set, the researcher

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proposes an attention-based LSTM that explores the potential aspect correlation and sentiment polarity in classification of sentiment aspects to get better accuracy [7]. This study contributes to the Tiktok application, which is very popular at this time, because of the interest of many users, so there is a data collection for Aspect-Based Sentiment analysis, the author will use the deep learning method Recurrent Neural Network with the Long Short-Term Memory (RNN – LSTM) model and the addition of word embedding BERT in sentiment analysis. The expected result is the performance of sentiment classification accuracy in every aspect consisting of Features, Business, and Content.

2. RESEARCH METHODOLOGY

2.1 Architecture System

In this research, it is expected to get the results of aspect classification and sentiment analysis with good performance or high accuracy. The classification into several aspects consisting of Features, Business, Content, and sentiment analysis for negative and positive classifications here using the Long Short-Term Memory (LSTM) method. This chapter focuses on the general research architecture, classification flow, and classification performance analysis. This ABSA process is shown in Figure 1.

Figure 1 Architecture System

2.2 Data Crawling

In this process, the researcher collected 10,000 review data from the google play store, data retrieval was carried out by crawling data on review sites regarding the TikTok application found on the Google Play Store. These reviews are comments from users of the Tiktok application which contain aspects of it, especially aspects of Features, Business, and Content and there are positive and negative charges in the comments.

2.3 Data Labeling

After crawling the data from the Google Play store with reviews in Indonesian, the next step is the process of labeling the division of words from the aspects used and labeling negative and positive sentiments manually. Determination of labels from each aspect using values, taking values based on the level of negative, neutral, and positive sentiments from comments, determining label values in this study are shown in Table 1.

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Table 1. Label value determination

Label	Description
-1	A negative value in an aspect
0	Not included in the aspect
1	A positive value in an aspect

The labeling of each aspect is carried out based on related vocabulary, for example, in" video nya bagus bagus" the data is included in the content aspect but not included in the feature and business aspect, and the determination of the vocabulary of each aspect in this study is shown in Table 2.

Table 2. Vocabulary determination

Feature	Business	Content
1. Login	1. Uang	1. Video
2. Edit	2. Untung	2. Hiburan
3. Aplikasi	3. Koin	3. Gambar
4. Koin	4. Poin	4. Informasi
5. Filter	5. Saham	5. Media
6. Profile	6. Invetasi	6. Viral
7. Follow		7. Fyp

The vocabulary used in labeling negative and positive sentiments in the study is shown in Table 3.

Table 3. vocabulary used

Positive	Negative
1. Baik	1. Jelek
2. Bagus	2. Kurang
3. Keren	3. Susah
4. Menarik	4. Sampah
5. Mantap	5. Rugi
6. Menghibur	6. Burik
7. Semangat	7. Mengecewakan

The vocabulary list in table 3 is used by the annotator in labeling the data as positive and negative, but the annotator continues to read the whole sentence to get the full meaning of the sentence. The results of labeling in this study are shown in Table 4.

Table 4. Data labeling results

Data	Feature	Business	Content	Description
mudah untuk ngedit video, menghibur	1	0	1	there is a vocabulary in the feature that is "edit" and has a positive score of "1" because there is a vocabulary of "menghibur", and there is vocabulary in the content, namely "video" and has a positive score of "1" because there is a vocabulary of "menghibur"
Sangat mengecewakan, katanya disuru undang teman biar dapat bonus uang eh pas mau masukin kode teman malah eror	0	-1	0	including negative into the business aspect because there is a pre-determined vocabulary in the business aspect
aplikasi nya bagus	1	0	0	including positive in the aspect of features, because there is a predetermined vocabulary in terms of content

2.4 Preprocessing

After labeling the data, the next step is data preprocessing, data preprocessing to handle unstructured data to be neater and cleaner from noise, there are three stages in this process, that is:

a. Case folding

At this stage, changing the form of writing to lowercase as well as removing punctuation marks and deleting emojis from the dataset, the results of the Case folding process can be seen in Table 5.

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Table 5. Case folding results

Input	Output
Aplikasi ini sangat bagus...Sangat menghibur, mohon jangan ada yang aneh^2 tik tok...Karna di tik tok saya banyak yang jorok^2 atau yang aneh...semoga aja makin di update...makin bagus😊😊🙏😊🥳	aplikasi ini sangat bagus…sangat menghibur, ….mohon jangan ada yang aneh tik tok….karna di tik tok saya banyak yang jorok atau yang aneh …semoga aja makin di update makin bagus 😊😊🙏😊🥳

b. Filtering

In this process, the data is cleared of punctuation and replaced with space characters. punctuation marks that are deleted are shown in table 6.

Table 6. Punctuation

Description	Punctuation
Dot	.
Exclamation mark	!
Question mark	?
Commas	,
Semicolon	;
Colon	:
Hyphen	-
slash mark	/
Quotation mark	“..”
Brackets	(..)
Apostrophe	‘

The goal is to make the training process simple, the results of the Filtering process can be seen in Table 7.

Table 7. Filtering result

Input	Output
Aplikasi ini sangat bagus...Sangat menghibur,..mohon jangan ada yang aneh^2 tik tok...Karna di tik tok saya banyak yang jorok^2 atau yang aneh...semoga aja makin di update...makin bagus😊😊🙏😊🥳	aplikasi ini sangat bagus sangat menghibur mohon jangan ada yang aneh tik tok karna di tik tok saya banyak yang jorok atau yang aneh semoga aja makin di update makin bagus

c. Stopwords removal

In this process, identification of the removal of unimportant words that are unrelated to sentiment analysis and saving important words will be carried out, stopword dictionary used from the sastrawi library, Stopwords dictionary is shown in Table 8

Table 8. Stopwords dictionary

Stopwords					
yang	kepada	dalam	kenapa	sedangkan	anu
untuk	oleh	bisa	yaitu	selagi	demikian
pada	saat	bahwa	yakni	sementara	tapi
ke	harus	atau	daripada	tetapi	ingin
para	sementara	hanya	itulah	apakah	juga
namun	setelah	kita	lagi	kecuali	nggak
menurut	belum	dengan	maka	sebab	mari
antara	kami	akan	tentang	selain	nanti
dia	sekitar	juga	demi	seolah	melainkan
dua	bagi	ada	dimana	seraya	oh
ia	serta	mereka	kemana	seterusnya	ok
seperti	di	sudah	pula	tanpa	seharusnya
jika	dari	saya	sambil	agak	sebetulnya
jika	telah	terhadap	sebelum	boleh	setiap
sehingga	sebagai	secara	sesudah	dapat	setidaknya
kembali	masih	agar	supaya	dsb	sesuatu
dan	hal	lain	guna	dst	pasti

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tidak	ketika	anda	kah	dll	saja
ini	adalah	begitu	pun	dahulu	toh
karena	itu	mengapa	sampai	dulunya	ya
walau	tolong	tentu	amat	apalagi	bagaimanapun

The results of the Stopward removal process can be seen in Table 7.

Table 9. Stopward removal result

Input	Output
“aplikasi” “ini” “sangat” “bagus” “sangat” “menghibur” “bisa” “tau” “apa” “aja” “mendapatkan” “hal” “yang” “lain” “yang” “menarik” “	“aplikasi” “sangat” “bagus” “sangat” “menghibur” “mendapatkan“ “hal“ “menarik”

2.5 Bert Word embedding

After the review data from the Google Play Store is cleaned, then word embedding is carried out. Word embeddings are d-dimensional spatial representations of words, encoded in vector numeric form. This vector specifies the words that appear in the specified word matrix. Given a word, the vector has a continuous model in its search and then feeds the information into a feed-forward neural network to predict the next possible word [8].

In his research [9] used pre-trained word embedding. system supports multiple word insertion such as Stanford GloVe, Google-News-Word2Vec, Godin, FastText, and Keras built-in embedding layers. Word insertion options are hyperparameters. In word vector representation, each sentence is represented as an R matrix. The results of this study use 10-fold cross-validation to evaluate the model. The F1 score is used to evaluate the performance of the aspect model. Due to the class imbalance present in this aspect of the data, the researcher decided to use the weighted average F1 score as a performance measure because it took into account class imbalances while calculating the scores. Researchers achieved a weighted average F1 score of 0.69. To measure the performance of the sentiment model, the researcher used the mean squared error and the R-score squared. The researcher's best sentiment model has an R squared score of 0.288 and predicts a sentiment score with an MSE of 0.112.

In this study, word embedding is used to find the relationship between words, and words contained in the training data using the Bidirectional Encoder Representations from Transformers (BERT) method. BERT is a pre-trained for large amounts of data, by combining the representation of words and sentences in a large transformer, in practice, the pre-trained BERT is divided into two parts, namely features and fine-tuning, BERT can produce better contextual token embedding. BERT fully understands the information from the text that is entered, from the important sentences that were entered previously, and then the sentence is rewritten to a shorter version and does not change the main meaning. The basic embedding architecture is shown in Figure 2.

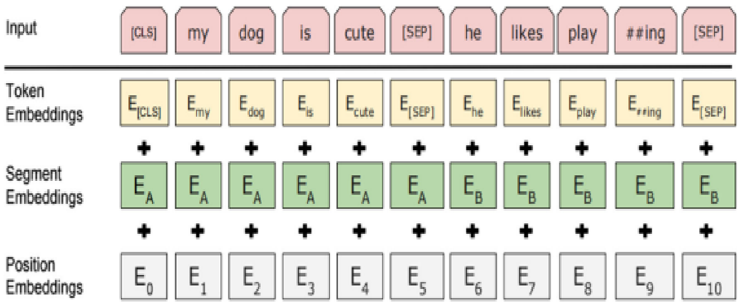

Figure 2. Basic embedding BERT

Embedding (BERT tokenizer), input embeddings consist of token embeddings, segmentation embeddings, and embedding positions [10]

In this study, word embedding BERT uses the pre-trained INDOBERT model, INDOBERT has been trained for more than 220 million words, collected from three main sources: (1) Indonesian Wikipedia (74 million words); (2) news articles from Kompas,10Tempo11, and Liputan612 (total 55 million words); and (3) the Indonesian Web Corpus (90 million words) [11]. After word embedding, then Feature Extractions are performed to convert the dataset in text form into vector form with a pad sequence. The illustration of the BERT tokenizer stages is shown in Figure 3.

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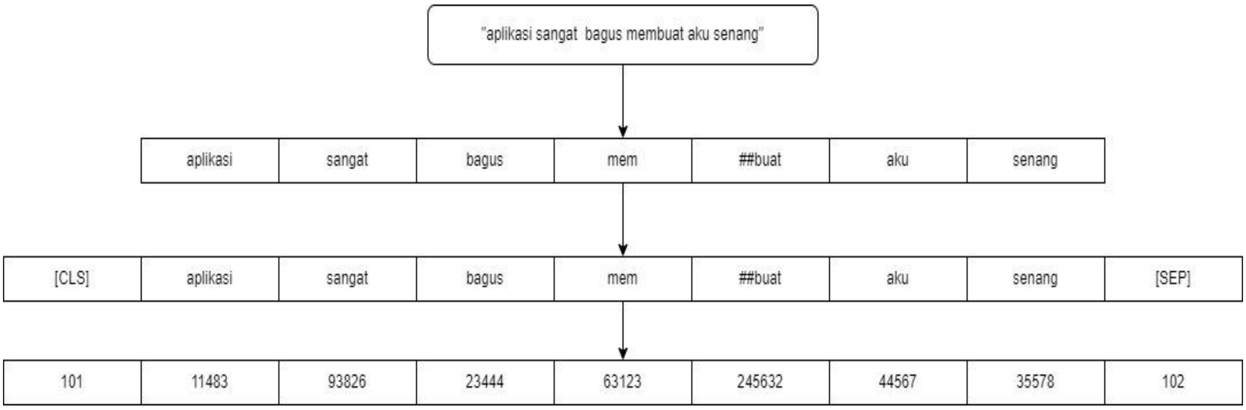

Figure 3. BERT Tokenizer Stages Llustration

After BERT gets input data in a certain format, then it is marked with a special token to mark ([CLS]) and end sentence separation ([SEP]).

2.6 LSTM Model Training

After the word embedding process is carried out, then divide the dataset into 70% for train data and 30% for test data, and sentiment classification in each aspect. Sentiment analysis is a classification in the form of text on an opinion, sentiment analysis can be classified into 2 parts, namely sentiment on products/films/services and sentiments expressed in social media such as on Twitter, Facebook, and Instagram [12].

Aspect-level sentiment analysis or commonly called Aspect-Based Sentiment Analysis (ABSA) is a type of sentiment analysis that can see all sentiments in every aspect [3]. In this study, the author will analyze the Aspect-Based Sentiment Analysis (ABSA) more deeply to get more optimal results and high accuracy.

The aspects used in this research are Features, Business, and Content to get sentiment polarity, sentiment analysis in this study is seen from the input of application users whether it is positive or negative, at this stage the researcher uses the highest accuracy for evaluation results using the deep learning method. Recurrent Neural Network with Long Short-Term Memory (RNN – LSTM) model.

Some studies show that Deep Learning models can automatically learn semantic and syntactic information by achieving better accuracy for sentiment analysis. Aspect-based sentiment analysis applies deep recurrent neural networks for opinion extraction [13]. Deep learning has been widely used in sentiment analysis because of its ability to learn features at a high level and find polarized opinions from the public about certain objects automatically. RNN is used for explicit sentiment analysis and modeling syntactic structure relationships in sentences, [14] proposes LSTM in predicting sentiment classification.

RNN is an artificial neural network designed to recognize sequential data, RNN is very suitable for handling sequential data such as sound, images, and text, RNN has an internal memory to store important things from what was previously inputted. [3]. RNN shows a fairly good performance in the process of classification and extraction of aspects. Its ability to recognize patterns remotely from the input data makes it a good potential to do NLP tasks [9].

RNNs have two very important features compared to feed-forward neural networks. First, unlike CNN, which has different parameters in each layer, RNN has the same parameters at each step, which then reduces the number of parameters needed to be studied. Both outputs depend on the previous state, RNN has a memory from previous computations, and RNN is superior in processing sequential data compared to CNN, However, simple RNN has major drawbacks in terms of missing gradient (gradient close to zero) or gradient burst (the gradient is extremely high) [8]. To solve this problem, Long Short-term Memory (LSTM) network was developed and got better performance. In its architecture, the LSTM has three gates in the memory state of the cell [15]. Figure 4 illustrates the standard LSTM architecture

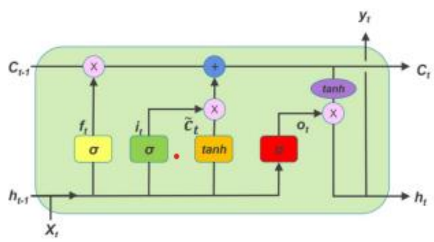

Figure 4. Basic LSTM

The LSTM structure has a cell vector value that is maintained at each step. An explicit gating mechanism is used in LSTM. Each LSTM consists of three binary gates, namely input gate (it), forget gate (ft), and output gate (ot). The input gate controls the memory cell in-process update, the forget gate controls the setting of the memory cell Back

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to zero, and the output gate controls the cell information flow visibility output $f_t = \sigma\left(W_f . [h_{t-1}, x_t]\right) + b_f$ [6]. A description of the parameters of the LSTM is shown in Table 8

Tabel 10. Description of parameters on LSTM

Parameter	Description
w_f	Weight vector of the forget gate layer
h_{t-1}	The previously hidden state vector
h_t	Output hidden state vector
x_t	Current input vector
b_f	Bias vector
i_t	Current input vector
o_t	Output vector
c_t	Output cell memory vector
c_{t-1}	Output cell memory vector
c_t	Current cell memory vector

LSTM with FL adopts the features of the ClausIE framework to divide long sentences into small meaningful sentences, is used for aspect-based sentiment analysis using the performance model developed, and experiments were carried out with and without word insertion techniques for feature extraction [16]. From the results, the researcher observes that the word insertion technique is very suitable for aspect-based sentiment analysis. Instead of classifying consumers reviewing sentences as positive and negative, the proposed LSTM with fuzzy logic model classified consumer products reviewing sentences as very negative, negative, positive, and very positive. The developed model was piloted on three publicly available data sets with 96.93% accuracy on ACPR, 83.82% accuracy on AVGR, and 90.92% accuracy on the CRAP data set. The proposed model also classifies consumer review sentences according to consumer location and current trends. The proposed model can be further extended for aspect-based sentiment analysis with very complex aspects.

Previous research [17] describes a simple but effective approach to combining lexicon information with an attentional LSTM model for ABSA to take advantage of the power of Deep Learning and existing linguistic resources so that the framework becomes more flexible and robust without the need for additional labeled data. The researcher also explored the effect of regulating attention vectors by introducing attention regulators to allow the network to have a wider "focus" on different parts of the sentence. The researcher describes a simple but effective approach to combining lexicon information with the LSTM model of concern for ABSA to take advantage of both the power of Deep Learning and existing linguistic resources so that the framework becomes more flexible and robust without the need for additional labeled data. The researcher also explored the effect of regulating attention vectors by introducing attention regulators to allow the network to have a wider "focus" on different parts of the sentence. Combining lexical features with networks without carefully designed mechanisms, the model is unable to take advantage of new information; and vice versa, the overall performance will decrease. although the lexicon only provides non-neutral polarity information for three words, the ATLX attention weights are less sparse and less diffuse than in the baseline.

In this study, the LSTM model used was built using the Keras library following previous research [6]. The parameters used are the default parameters of the LSTM, the performance of the proposed model is analyzed by training the size of the input embedding layer with 64 and 128, this model provides better accuracy for the length of 64 words embedding vector for input on three benchmark data sets. The memory unit is used to remember the words from the sentence review input. The proposed LSTM is designed with 100 memory units remembering words to understand long review paragraphs. Three nodes are selected for the output layer to generate a sentiment score (positive, negative, and neutral).

3. RESULT AND DISCUSSION

3.1 Performance Evaluations

In Performance Evaluations, sentiment classification is carried out from each predetermined aspect. At this stage, we discuss the results of the model that has been trained previously so that it gets good accuracy on the sentiment classification of each aspect.

As a result, the LSTM takes the input and the input label adjusts the perceptron weights for each node and layer. then calculate the final weight of the three nodes in the output layer. To predict, LSTM takes validation data as input based on the weights that have been calculated in the fitting process. After calculations on the output, the model returns the final weights between the three nodes. And then I choose a higher value as the final prediction result

3.3.1 Feature

The feature aspect results of the classification of sentiment on the feature aspect get an accuracy score of 0.85 and data loss of 0.27, based on the resulting sentiment, the TikTok application on the feature aspect produces a positive sentiment of 693, and a negative of 305. The evaluation matrix is used to see the value of accuracy and the number of

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errors in sentiment classification on aspects. The sentiment classification evaluation matrix on the feature aspect is shown in Figure 4.

Figure 5. Feature Aspect Evaluation Matrix

From these results, positive sentiment has an accuracy score of 19.23 with a data loss of 0.53 and negative sentiment of 7.23 with a data loss of 0.67.

3.3.2 Business

The business aspect result of the classification of sentiment on the business aspect gets an accuracy score of 0.94 and data loss of 0.11, based on the resulting sentiment, the TikTok application on the business aspect produces a positive sentiment of 86, negative of 326. The evaluation matrix of sentiment classification on the business aspect is shown in Fig. Figure 4.

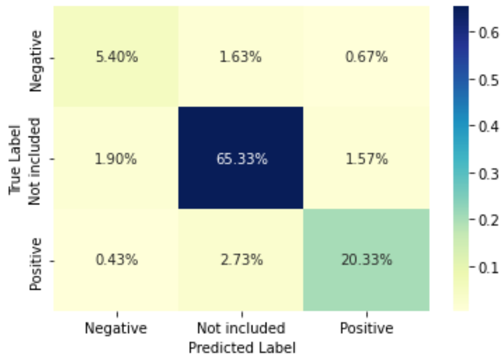

Figure 6. Business Aspect Evaluation Matrix

From these results, positive sentiment has an accuracy score of 1.97 with a data loss of 1.30 and negative sentiment of 8.27 with a data loss of 0.57.

3.3.3 Content

The content aspect result of the sentiment classification on the content aspect gets an accuracy score of 0.91 and data loss of 0.19, based on the sentiment generated, the TikTok application on the content aspect produces a positive sentiment of 677, a negative of 232. The evaluation matrix of sentiment classification on the feature aspect is shown in Fig. Figure 4.

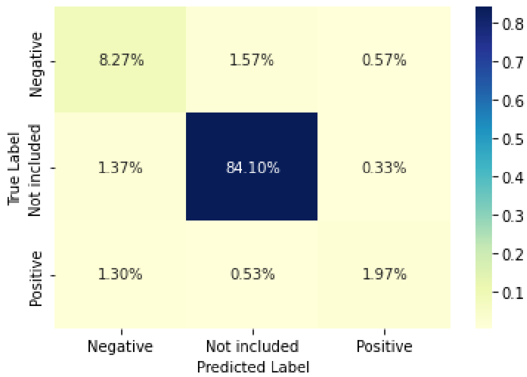

Figure 7. Content Aspect Evaluation Matrix

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From these results, positive sentiment has an accuracy score of 20.33 with a data loss of 0.43 and negative sentiment of 7.40 with a data loss of 0.67.

The accuracy of each aspect has a different value, the highest accuracy is obtained in the business aspect of 0.94 while the lowest accuracy value is found in the feature aspect with an accuracy value of 0.85, the comparison of the accuracy of each aspect is shown in table 5

Tabel 11. Comparison of results

Aspect	Positive	Not included in the aspect	Negative	accuracy
Feature	23.1 %	66.74 %	10.16 %	0.85 %
Business	22.57 %	69.69 %	7.73 %	0.95 %
Content	2.87 %	86.2 %	10.94 %	0.91 %

4. CONCLUSION

In this study, the authors propose Deep learning for ABSA (Aspect-based sentiment analysis). This study shows good results on sentiment classification from every aspect using 10,000 data taken from the google play store with aspects of Features, Business, and Content, deep learning method used is the Recurrent Neural Network with Long Short-Term Memory (RNN – LSTM) model. and the addition of word embedding BERT with a pre-training model, namely IndoBERT. The scenario used in this research is to classify the sentiment of each aspect that has been determined. The results of this study get the accuracy value on the sentiment classification of each aspect not too much different. In the Business aspect, the highest accuracy value is 0.95, in the Content aspect, the accuracy value is 0.91 while in the Features aspect, the lowest value is 0.85. Judging from the accuracy obtained, the model used has a pretty good performance.

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