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Graph-Based Semi-Supervised Deep Learning for Indonesian Aspect-Based Sentiment Analysis

Ahmad Abdul Chamid [1,*], Widowati [2] and Retno Kusumaningrum [3]

[1] Doctoral Program in Information Systems School of Postgraduate Studies, Diponegoro University, Semarang 50275, Indonesia
[2] Department of Mathematics, Faculty of Science and Mathematics, Diponegoro University, Semarang 50275, Indonesia
[3] Department of Informatics, Faculty of Science and Mathematics, Diponegoro University, Semarang 50275, Indonesia
* Correspondence: chamid@students.undip.ac.id

Abstract: Product reviews on the marketplace are interesting to research. Aspect-based sentiment analysis (ABSA) can be used to find in-depth information from a review. In one review, there can be several aspects with a polarity of sentiment. Previous research has developed ABSA, but it still has limitations in detecting aspects and sentiment classification and requires labeled data, but obtaining labeled data is very difficult. This research used a graph-based and semi-supervised approach to improve ABSA. GCN and GRN methods are used to detect aspect and opinion relationships. CNN and RNN methods are used to improve sentiment classification. A semi-supervised model was used to overcome the limitations of labeled data. The dataset used is an Indonesian-language review taken from the marketplace. A small part is labeled manually, and most are labeled automatically. The experiment results for the aspect classification by comparing the GCN and GRN methods obtained the best model using the GRN method with an F1 score = 0.97144. The experiment for sentiment classification by comparing the CNN and RNN methods obtained the best model using the CNN method with an F1 score = 0.94020. Our model can label most unlabeled data automatically and outperforms existing advanced models.

Keywords: graph convolutional network; graph recurrent network; semi-supervised; aspect-based sentiment analysis

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1. Introduction

The user reviews on the marketplace are written freely and independently. So that the review data can be used to determine the assessment of opinions and sentiments that appear on the products being sold, sentiment analysis can be used to find out an opinion that has been written in a review [1]. In sentiment analysis, there are several levels; namely, the sentence or document level is used to find out the overall opinion of a review [2,3], and the aspect level is used to find out several opinions contained in a review, and each opinion can have sentiment polarity [4–6]. Deep-learning models have been developed for sentiment analysis focusing on a document or sentence level [7,8] and aspect level [6,9,10]. In addition, aspect-based sentiment analysis (ABSA) can be used to obtain opinions and sentiment polarity in a review [11].

Previous research has developed ABSA using deep learning. For example, [12] using the attention mechanism is claimed to improve the LSTM model for Indonesian ABSA. The convolutional neural network (CNN) method can extract high-level semantic features. The feature extraction results are entered in a bidirectional long short-term memory (Bilstm) layer to obtain a contextual feature representation of a text. The results of experiments using public datasets are claimed to have increased for ABSA [13]. Researchers generally develop deep-learning models by utilizing labeled data, but obtaining labeled data is very difficult, so a particular approach is needed to solve it [14].

Several approaches have been used to develop deep-learning models, namely supervised learning [15–17], unsupervised learning [18–21], and semi-supervised learning [22–24]. The challenge in developing deep-learning models lies in labeled data [25]. Obtaining labeled data is challenging and requires experts [26,27]. The semi-supervised learning approach can overcome data-labeling problems by utilizing little labeled data and many unlabeled data [28].

Semi-supervised has been used to develop ABSA by utilizing deep-learning algorithms [29,30], while semi-supervised deep learning for Indonesian ABSA has not been widely developed. So, the development of ABSA Indonesia is open using semi-supervised deep learning. However, much research on Indonesian ABSA is still trying to improve accuracy in extracting aspects and polarity of sentiment [12,31–33]. A graph-based approach has been widely used to overcome problems in increasing accuracy in developing ABSA English models [9,34]. A graph-based approach is used with several deep-learning methods to build ABSA models in English, such as graph neural network [35,36], graph convolutional neural network [34,37], and graph attention network [38,39].

In this study, we develop graph-based semi-supervised deep learning to improve aspect-based sentiment analysis in Indonesian. Semi-supervised learning is used to overcome problems in data labeling, while a graph-based approach is used to enhance accuracy results in developing deep-learning models for Indonesian ABSA.

2. Literature Review

Several studies discuss different problems in Indonesian-language ABSA. For example, Nayoan et al. [40] utilized Indonesian tourism review data taken from the Tripadvisor travel website, and the ABSA model was developed using convolutional neural networks (CNN) to extract aspects and sentiments from tourism reviews. Several experiments were carried out to obtain the best model by comparing the CNN, CNN-LSTM, and CNN-GRU models. The result was that CNN combined with the POS tag outperformed other models.

Tedjojuwono et al. [41] developed a dynamic dashboard to display restaurant information in Indonesia, using data obtained from online restaurant reviews on the Tripadvisor platform. The approach used is semi-supervised ABSA. Although machine-learning tools are used to extract aspects and sentiments, the accuracy analysis results are less than ideal due to the lack of negative sentiment datasets that affect the model during training.

Cendani et al. [12] introduce Indonesian ABSA using a long short-term memory (LSTM) model with an attention mechanism. Indonesian-language hotel review data are used to develop the model. The data obtained consist of five aspects and three sentiments. Several experiments with different parameters resulted in the best model performance with an F1 value of 0.7628. The attention mechanism is stated to improve the LSTM model for ABSA.

ABSA has been used to determine the character traits of legislative candidates in the Indonesian presidential election and has been studied [42] by utilizing Twitter data during the Indonesian presidential election campaign period in 2018 and 2019. The Indonesian-language tweet text data are annotated with labels as candidate targets and aspects as character traits and sentiments. Furthermore, a comparison of machine-learning algorithms is used to classify datasets automatically. The comparison results show that the support vector machine algorithm performs better than naïve Bayes and k-nearest neighbor.

Yanuar et al. [43] utilize reviews to develop a decision support system in the tourism sector. The data used come from the TripAdvisor platform. ABSA is used to overcome problems in analyzing the complexity of Indonesian tourist attractions' reviews. Aspect extraction is an essential component in developing ABSA. Bidirectional encoder representations from transformers (BERT) is used to extract aspects by training the model using Indonesian-language review sentences. BERT successfully extracted aspects with an accuracy value of 0.799 and an F1 value of 0.738.

CNN and B-LSTM were used to improve ABSA in reviews of Indonesian-language restaurants [32] by adapting research in which F1 reached the highest value in SemEval 2016. The experiment results obtained aspect classification with an F1 value of 0.870, opinion extraction with an F1 value of 0.787, and sentiment polarity classification with an F1 value of 0.764.

ABSA has been used [31] for aspect detection and sentiment classification. The Indonesian review from the online marketplace Tokopedia was used as a two-stage experiment. The first stage performs aspect detection by comparing two deep neural network models using a gated recurrence unit (GRU) and Fully Connected. The second stage performs sentiment classification by comparing the deep neural network approach using sentiment lexicon and CNN. The developed model is claimed to be better than previous research using SVM and rule-based methods.

The English ABSA has been developed to analyze restaurant, laptop, and Twitter reviews [34]. The graph convolutional network (GCN) and recurrent neural network (RNN) methods were used to develop ABSA by comparing five datasets. The results stated that the developed model could outperform the existing model, and the gate mechanism was said to be able to improve performance with an F1 score of 66.64~76.80%.

Chakraborty [44] used the graph neural network (GNN) method for ABSA in English. Graph Fourier transform-based network with the spectral domain is proposed to develop ABSA. The dataset used is laptops, restaurants, men's t-shirts, and television reviews. Based on the test results, it is stated that the developed model is able to obtain the best results on the laptop and restaurant domain dataset. In addition, the proposed model can be competitive on other datasets from the e-commerce domain, with the highest F1 score of 78.77.

The relational graph attention network (R-GAT) was used to develop ABSA in English [39]. First, the dependency tree is used to detect aspects that are connected with the word opinion in the review, and then R-GAT is used to predict the sentiment of each aspect obtained. The experimental results using the SemEval 2014 and Twitter datasets show that the relationship between aspects and opinions is well detected. In addition, the R-GAT is stated to be able to improve the model performance with an F1 score of 81.35.

The dual graph convolutional networks (DualGCN) model was developed in ABSA to simultaneously obtain the syntactic structure and semantic relationships [45]. The SynGCN module is used to reduce dependency parsing errors while obtaining semantic relationships using the SemGCN module. After testing using a dataset from SemEval 2014 (domain: restaurant and laptop) and Twitter, the results were obtained with the highest F1 score of 78.08. Therefore, the DualGCN model is declared to outperform existing methods.

The Sentic GCN model was developed for ABSA [46] by utilizing the public domain laptop and restaurant dataset from SemEval 2014, SemEval 2015, and SemEval 2016. Graph convolutional networks are integrated with dependency trees and affective knowledge to improve sentence dependency graphs so that words containing contextual, opinion, and aspects can be detected. The experimental results stated that the developed model could outperform the existing method, with the highest F1 score of 75.91.

Table 1 summarizes related research in aspect-based sentiment analysis in Indonesian and English.

Table 1. The summary of related research.

Paper	Model	Dataset	Result
Aspect-Based Sentiment Analysis in Indonesia			
Nayoan et al. [40]	CNN + POS tag	Tripadvisor (Indonesian tourism review)	Accuracy: sentiment analysis = 0.9522 and aspect category = 0.9551

Table 1. *Cont.*

Paper	Model	Dataset	Result
Aspect-Based Sentiment Analysis in Indonesia			
Cendani et al. [12]	LSTM + attention mechanism	Indonesian hotel review	F1 score = 0.7628
Manik et al. [42]	Support vector machine	Twitter (Indonesian presidential election campaigns in 2018 and 2019)	Accuracy: Aspect = 68.41% Sentiment = 87.56%
Yanuar et al. [43]	BERT	Tripadvisor (Indonesian tourist spot review)	F1 score = 0.738
Cahyadi and Khodra [32]	CNN and B-LSTM	Indonesian restaurant reviews	F1 score: Aspect = 0.870 Sentiment = 0.764
Ilmania et al. [31]	GRU, lexicon, and CNN	Indonesian review from the online marketplace Tokopedia	F1 score = 0.8855
Aspect-Based Sentiment Analysis in English			
Kim et al. [34]	GCN + RNN	Restaurant reviews of SemEval 2014, 2015, and 2016. Laptop review of SemEval 2014. Twitter review.	F1 score = 66.64~76.80%
Chakraborty [44]	Spectral temporal GNN	Laptop and restaurant review from SemEVal-14. Men's t-shirt and television review.	F1 score = 78.77
Wang et al. [39]	Relational graph attention network (R-GAT)	SemEval 2014 (domain: restaurant and laptop) and Twitter	F1 score = 81.35
Li et al. [45]	Dual GCN	SemEval 2014 (domain: restaurant and laptop) and Twitter	F1 score = 78.08
Liang et al. [46]	Sentic GCN	SemEval 2014, SemEval 2015, and SemEval 2016 (domain laptop and restaurants)	F1 score = 75.91

Contribution

After conducting a literature review, several limitations were identified. Research in recent years related to Indonesian ABSA has widely applied deep-learning algorithms [12,31,32,40,43] and used machine-learning algorithms [42]. In general, previous research in the Indonesian-language domain has not tried to use a graph approach to develop the Indonesian-language ABSA. While the development of ABSA in English has generally used a deep-learning graph approach, the datasets used are generally public datasets which, of course, are labeled data. Based on the literature review, there are still opportunities to improve the model in the Indonesian-language ABSA task.

Contributions in this study can be summarized as follows:

1. Graph dependency parse is used to extract aspect and opinion relationship words.
2. The extraction results are used to assist the multi-label labeling process. In addition, semi-supervised learning is used to overcome problems in data labeling by utilizing little labeled data and many unlabeled data.
3. GCN and GRN are used for aspect and opinion extraction. CNN and RNN are used for sentiment classification.
4. The experimental results show an improvement in our proposed model in the Indonesian-language ABSA task.

3. Materials and Methods

This research was conducted in several stages: data collection, semi-supervised, build model, automatic labeling, and performance evaluation. The whole process in this study is shown in Figure 1.

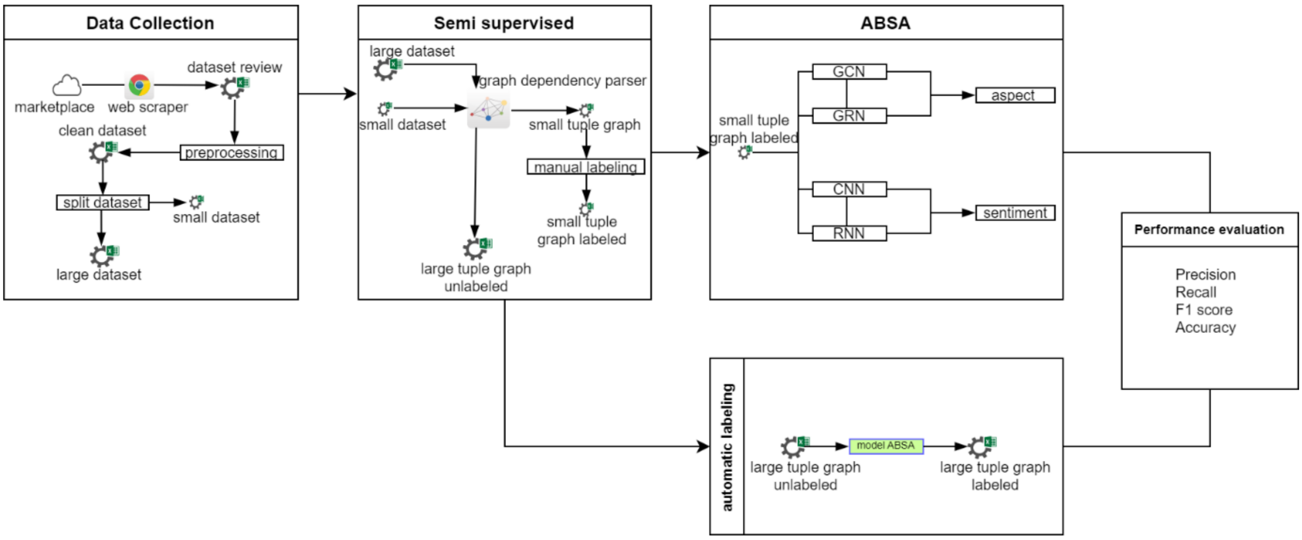

Figure 1. Research methods.

3.1. Data Collection

In this study, we use review data for men's t-shirts from the Indonesian marketplace. The data are obtained by scraping using Chrome Web Scraper tools. The scraping results obtained 15,237 data from product reviews on the Indonesian marketplace. The review data obtained were preprocessed by tokenization, stop-word removal, and stemming. After preprocessing, the data are split with details of 3894 data being labeled manually and 11,343 data being labeled automatically.

3.2. Semi-Supervised and Graph-Based

The semi-supervised principle uses little labeled data and many unlabeled data. Graph dependency parse is used to extract aspect and opinion words from 3894 data after being extracted to 4307 data. A data-labeling process follows the result. The results of data labeling, for example, are shown in Table 2.

Table 2. An example of dependency parse result and labeled data.

Review	Aspect	Opinion	True Tuple	Sentiment	Class Aspect
responnya lama pengiriman cepat bahan lembut tapi ukuran kekecilan dan warna kusam	respon	lama	1	−1	pelayanan
responnya lama pengiriman cepat bahan lembut tapi ukuran kekecilan dan warna kusam	pengiriman	cepat	1	1	pengiriman
responnya lama pengiriman cepat bahan lembut tapi ukuran kekecilan dan warna kusam	bahan	lembut	1	1	bahan
responnya lama pengiriman cepat bahan lembut tapi ukuran kekecilan dan warna kusam	ukuran	kekecilan	1	−1	ukuran
responnya lama pengiriman cepat bahan lembut tapi ukuran kekecilan dan warna kusam	warna	kusam	1	−1	warna

Figure 2 shows an example of using dependency parse using the stanza library (http://stanza.run/ (accessed on 17 October 2022) in the review sentence: "responnya lama pengiriman cepat bahan lembut tapi ukuran kekecilan dan warna kusam", which in English is "the response is long, fast delivery, soft material but the size is too small and the color is dull".

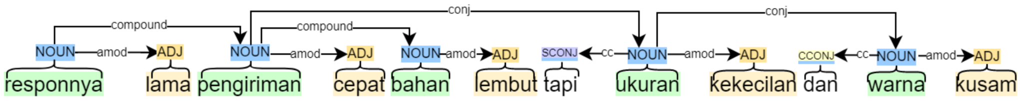

Figure 2. An example of using dependency parse.

The result of using dependency parse is made in an adjacency matrix, as shown in Figure 3.

Adjacency Matrix												
	responnya	lama	pengiriman	cepat	bahan	lembut	tapi	ukuran	kekecilan	dan	warna	kusam
responnya	0	amod	compound	0	0	0	0	0	0	0	0	0
lama	0	0	0	0	0	0	0	0	0	0	0	0
pengiriman	0	0	0	amod	compound	0	0	conj	0	0	0	0
cepat	0	0	0	0	0	0	0	0	0	0	0	0
bahan	0	0	0	0	0	amod	0	0	0	0	0	0
lembut	0	0	0	0	0	0	0	0	0	0	0	0
tapi	0	0	0	0	0	0	0	0	0	0	0	0
ukuran	0	0	0	0	0	0	cc	0	amod	0	conj	0
kekecilan	0	0	0	0	0	0	0	0	0	0	0	0
dan	0	0	0	0	0	0	0	0	0	0	0	0
warna	0	0	0	0	0	0	0	0	0	cc	0	amod
kusam	0	0	0	0	0	0	0	0	0	0	0	0

Figure 3. An example adjacency matrix of the dependency parse.

The results of the adjacency matrix are visualized in graph form using the library network (https://networkx.org/documentation/stable/ (accessed on 17 October 2022), as shown in Figure 4. The extraction results from the review sentences can be seen to have relationships between words and contain aspects and opinions. They are making it more accessible in the data-labeling process.

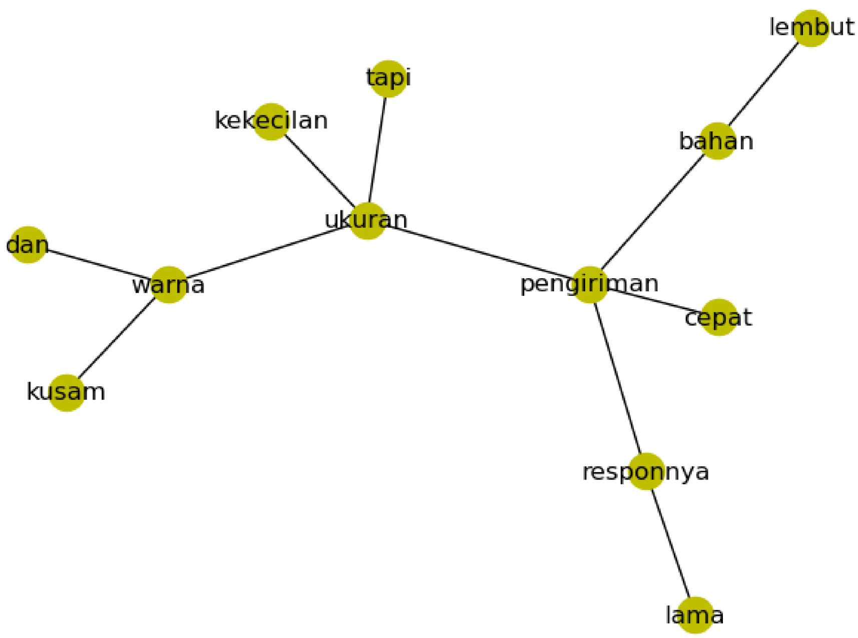

Figure 4. An example of graph networks.

The research started using a simple graph [47] $G = (V, E, A)$, including a set of m nodes V, one set of n edges E, and an adjacency matrix $A \in R^{mXm}$ containing the weight of edges A_{ij}. The value of A_{ij} is shown in Equation (1).

$$A_{ij} = \begin{cases} a, & if\ v_i, v_j \in V,\ and\ e_{ij} \in E, \\ 1, & if\ v_i = v_{j,} \\ 0, & otherwise \end{cases} \tag{1}$$

a is the weight of the edge, and $a = 1$ for unweighted graphs. A node v_i has a set of neighbors $N(i)$ that is defined as $N(i) = \{v_j \in V | (v_i, v_j) \in E\}$. Graph G has a node feature matrix $N \in R^{mXd_n}$, where each row $n \in N$ represents the feature vector of the node $v_i \in V$.

The aspect and opinion columns result from extracting review sentences using a dependency parse. True tuple, sentiment, and class aspects are performed manually. A true tuple consists of 1 = there are aspects, 0 = there is no aspect. Sentiment consists of 1 = positive, 0 = no sentiment, and -1 = negative. The class aspect consists of material (*bahan*), size (*ukuran*), color (*warna*), sewing (*jahitan*), quality (*kualitas*), price (*harga*), delivery (*pengiriman*), and service (*pelayanan*).

The statistical dataset used to build the model is shown in Table 3.

Table 3. The statistics of labeled data.

Aspect	Total	Positive	Negative
bahan	1291	615	629
kualitas	240	142	89
pelayanan	503	248	152
jahitan	123	101	21
harga	207	176	26
ukuran	479	127	332
warna	547	112	152
pengiriman	283	92	182

3.3. Build Model

In this study, several scenarios will be used. Scenario 1 builds an ABSA model using graph convolutional network (GCN) and graph recurrent network (GRN) to detect aspects. GCN and GRN architecture for aspect detection as shown in Figures 5 and 6.

The GCN architecture to detect aspects is built using a sequential model, consisting of input layers with 10,000, 32, convolution layers with filters = 8 activation = relu, max-pooling layers using pool_size = 2, flatten layers, hidden layers with 24 activation = sigmoid, dropout layers = 0.5, and output layer = 1 activation = sigmoid.

The GRN architecture for detecting aspects is built using a sequential model, consisting of input layer = 5000, 12, LSTM layer = 24, hidden layer = 24 activation = relu, and output layer = 1 activation = sigmoid.

Scenario 2 builds the ABSA model using CNN and RNN for sentiment classification. CNN and RNN architecture are used for sentiment classification as shown in Figures 7 and 8.

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding (Embedding)       (None, 7, 32)             320000

 conv1d (Conv1D)             (None, 5, 8)              776

 max_pooling1d (MaxPooling1D  (None, 2, 8)             0
 )

 flatten (Flatten)           (None, 16)                0

 dense (Dense)               (None, 24)                408

 dropout (Dropout)           (None, 24)                0

 dense_1 (Dense)             (None, 1)                 25

=================================================================
Total params: 321,209
Trainable params: 321,209
Non-trainable params: 0
_________________________________________________________________
```

Figure 5. GCN architecture for aspect.

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding (Embedding)       (None, 7, 12)             60000

 lstm (LSTM)                 (None, 24)                3552

 dense (Dense)               (None, 24)                600

 dense_1 (Dense)             (None, 1)                 25

=================================================================
Total params: 64,177
Trainable params: 64,177
Non-trainable params: 0
_________________________________________________________________
```

Figure 6. GRN architecture for aspect.

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding (Embedding)       (None, 20, 16)            320000

 conv1d (Conv1D)             (None, 18, 8)             392

 max_pooling1d (MaxPooling1D  (None, 9, 8)             0
 )

 flatten (Flatten)           (None, 72)                0

 dense (Dense)               (None, 24)                1752

 dropout (Dropout)           (None, 24)                0

 dense_1 (Dense)             (None, 1)                 25

=================================================================
Total params: 322,169
Trainable params: 322,169
Non-trainable params: 0
_________________________________________________________________
```

Figure 7. CNN architecture for sentiment.

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 embedding (Embedding)       (None, 20, 16)            320000

 lstm (LSTM)                 (None, 24)                3936

 dense (Dense)               (None, 24)                600

 dropout (Dropout)           (None, 24)                0

 dense_1 (Dense)             (None, 1)                 25

=================================================================
Total params: 324,561
Trainable params: 324,561
Non-trainable params: 0
_________________________________________________________________
```

Figure 8. RNN architecture for sentiment.

CNN architecture for sentiment classification is built using a sequential model, consisting of an input layer with 20,000, 16, convolution layer with activation = relu, max pooling layer using pool_size = 2, flatten layer, hidden layer = 24 with activation = sigmoid, dropout layer = 0.5, and output layer = 1 with activation = sigmoid.

The RNN architecture for sentiment classification is built using a sequential model, consisting of input layer = 20,000, 16, LSTM layer = 24, hidden layer = 24 with activation = sigmoid, dropout layer = 0.5, and output layer = 1 with activation = sigmoid.

3.4. Automatic Labeling

Before automatic labeling, 11.343 data were extracted using the stanza library to 11,270 data. The GCN and GRN models that have been built are used for aspect labeling, and the CNN and RNN models are used for sentiment labeling automatically for 11,270 data.

3.5. Performance Evaluation

To evaluate the performance of the model, a confusion matrix was used [47] as in (2)–(5).

$$Accuracy = \frac{(TP + TN)}{(TP + FN + TN + FP)} \tag{2}$$

$$Precision = \frac{TP}{(TP + FP)} \tag{3}$$

$$Recall = \frac{TP}{(TP + FN)} \tag{4}$$

$$F1\ Score = 2 * \frac{Recall * Precision}{Recall + Precision}. \tag{5}$$

TP is a true positive, TN is a true negative, FN is a false negative, and FP is a false positive.

4. Results and Discussion

The GCN and GRN model training process for aspect classification uses parameters, as shown in Table 4. Parameters are used to obtain the right combination of parameters to obtain the best model. The model training process for aspect classification using GCN and GRN is visualized as shown in Figures 9 and 10. If the best model is obtained, the training process will stop. For example, the GRN model training process uses an epoch val =100, but at epoch 59, the training process has stopped because the model with the best accuracy has been obtained. In the training process, the GCN model uses an epoch value =100. After epoch 9, the training process stopped because the best model had been obtained with the highest accuracy.

Table 4. The parameters of the training model GCN and GRN.

Model	Number of Units	Batch Size	Number of Filters	Kernel Size	Dropout
GCN	321,209	32	8	3	0.5
GRN	64,177	32	-	-	-

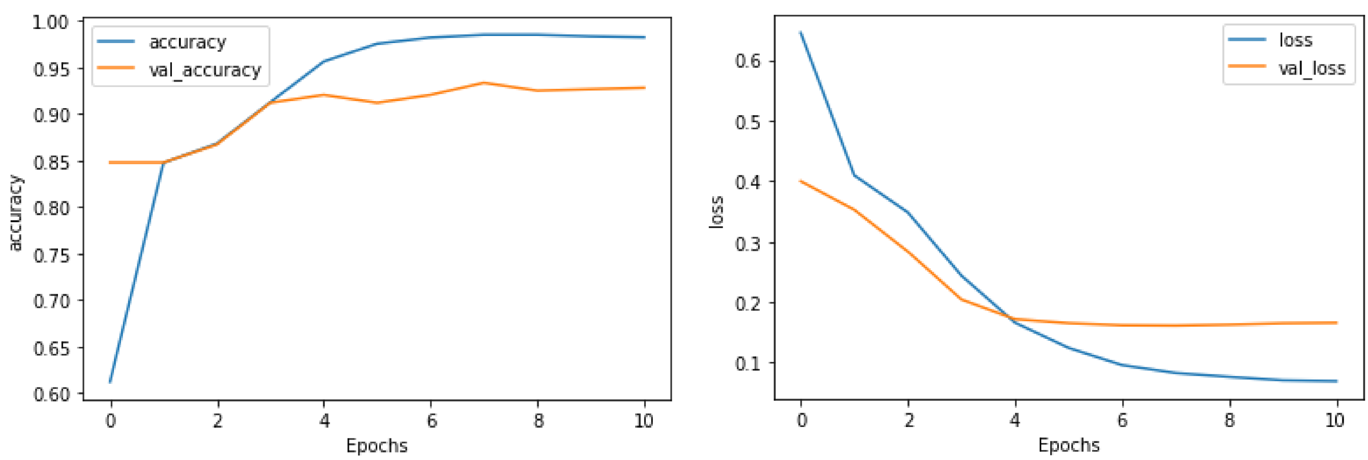

Figure 9. The data training process using GCN.

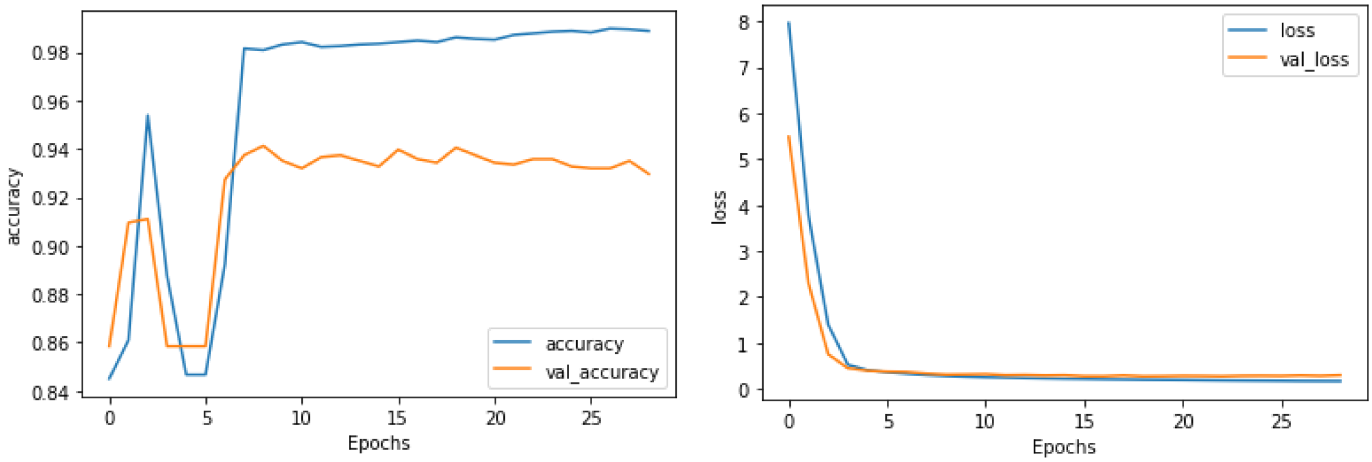

Figure 10. The data training process using GRN.

The CNN and RNN model training process for sentiment classification is shown in Figures 11 and 12. The parameters used in the sentiment classification model training process are shown in Table 5. Based on the visualization of the training model process, the highest accuracy value and the slightest loss value can be seen. The CNN and RNN model training process uses an epoch value = 100. In the process, the training continues until it reaches 100 epochs, and the best model is obtained with the highest accuracy.

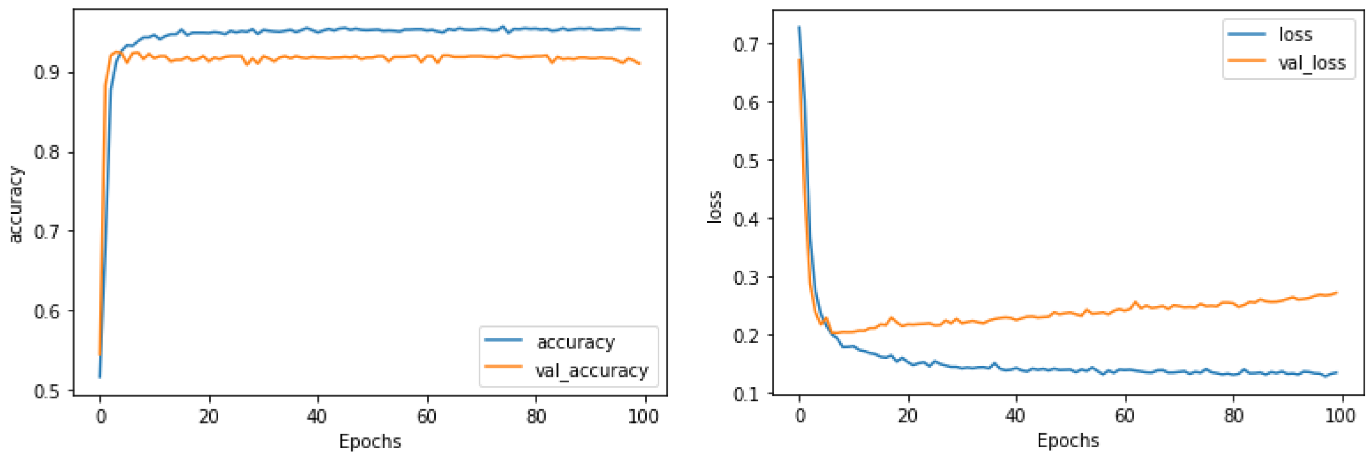

Figure 11. The data training process using CNN.

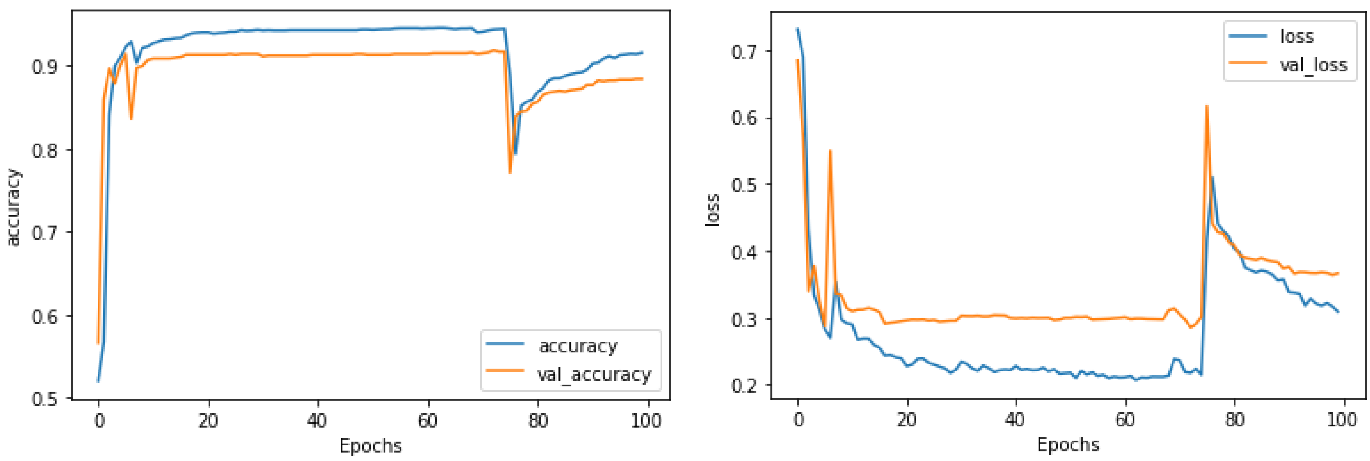

Figure 12. The data training process using RNN.

Table 5. The parameters of the training model CCN and RRN.

Model	Number of Units	Batch Size	Number of Filters	Kernel Size	Dropout
CNN	322,169	32	8	3	0.5
RNN	324,561	32	-	-	0.5

In Figures 10 and 12, during the training process, there is a decrease in the accuracy curve and an increase in the loss curve because the use of Adam optimization allows the model to escape local maximum accuracy. So, from epoch 0 to before 5, the model is at a local minimum. There is no difference in the problem of loss because the loss calculation is carried out in a macro-average manner, while validation is carried out in binary. In epoch 80, due to the use of the Adam evaluation model, the stagnation in the previous epoch made the model try to move areas, fearing it would become stuck at the local maximum. At a loss, a model evaluation is also carried out to avoid a local minimum.

After carrying out the training process for the GCN and GRN models for aspect classification and CNN and RNN models for sentiment classification, it is followed by evaluating the performance of each model. The results of the performance evaluation of the GCN and GRN models use a confusion matrix, as shown in Figures 13 and 14. The results of the performance evaluation of the GCN model are known so that the model can predict which aspect should be predicted correctly as aspect = 0.98 and which should not be predicted as not aspect = 0.92. The results of the GRN model are known to predict what should be predicted as aspect = 0.98 and which should not be predicted, not aspect = 0.91. The results of the calculation of the GCN and GRN model score evaluations for each aspect are shown in Tables 6 and 7.

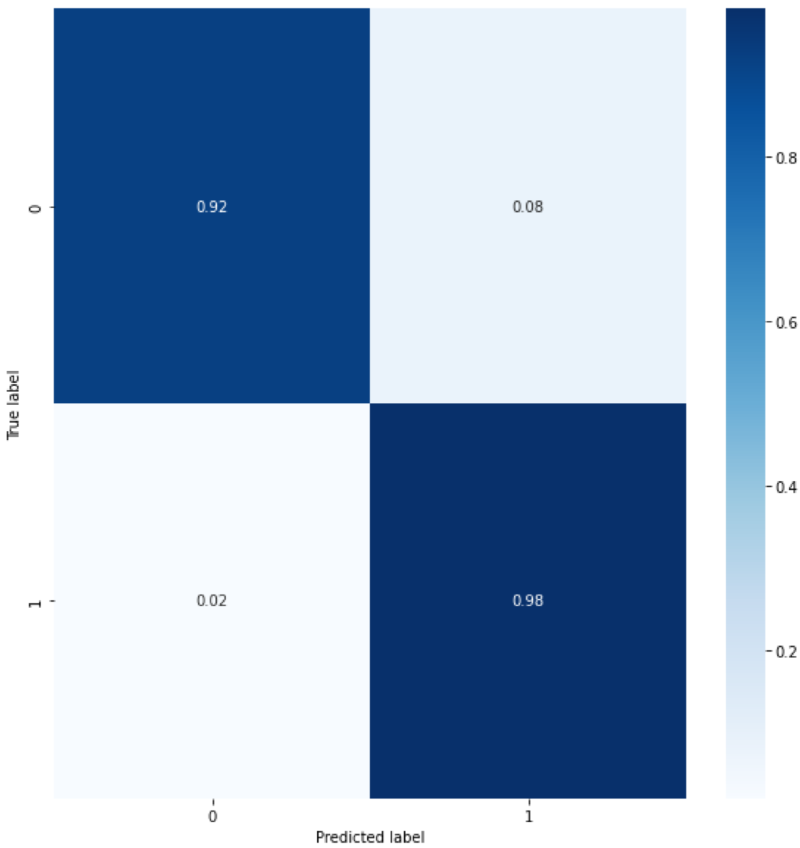

Figure 13. The result of the confusion matrix GCN.

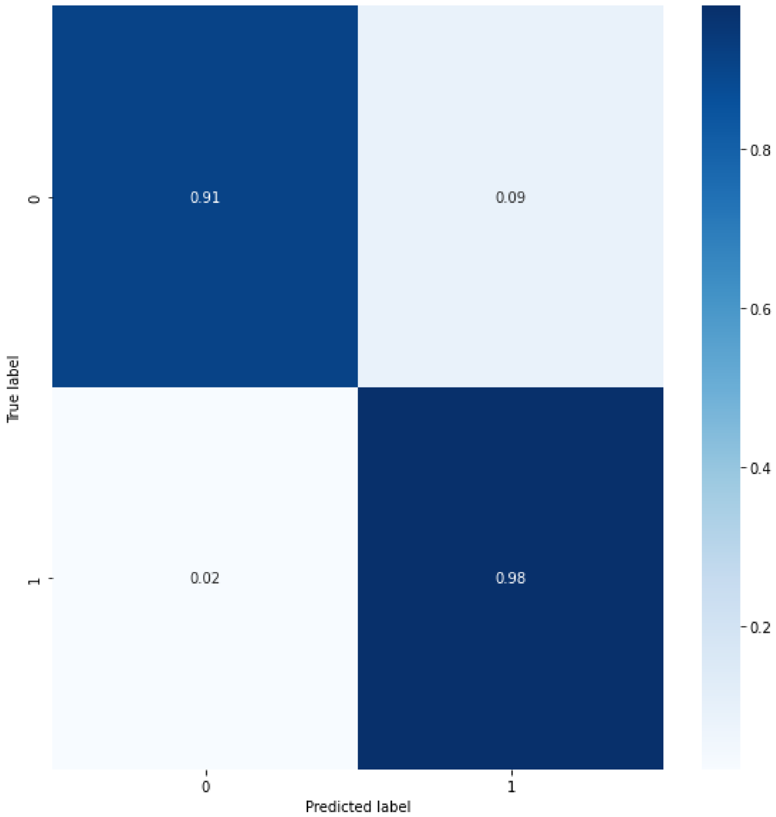

Figure 14. The result of the confusion matrix GRN.

Table 6. The experiment results of the GCN model in every aspect.

Aspect	Accuracy	Precision	Recall	F1 Score
bahan	0.98141	0.98141	0.98141	0.98141
kualitas	0.98750	0.98750	0.98750	0.98750
pelayanan	0.94632	0.94632	0.94632	0.94632
jahitan	0.98374	0.98374	0.98374	0.98374
harga	0.98068	0.98068	0.98068	0.98068
ukuran	0.97077	0.97077	0.97077	0.97077
warna	0.98355	0.98355	0.98355	0.98355
pengiriman	0.96820	0.96820	0.96820	0.96820

Table 7. The experiment results of the GRN model in every aspect.

Aspect	Accuracy	Precision	Recall	F1 Score
bahan	0.98296	0.98296	0.98296	0.98296
kualitas	0.98750	0.98750	0.98750	0.98750
pelayanan	0.97416	0.97416	0.97416	0.97416
jahitan	0.98374	0.98374	0.98374	0.98374
harga	0.97585	0.97585	0.97585	0.97585
ukuran	0.96869	0.96869	0.96869	0.96869
warna	0.98720	0.98720	0.98720	0.98720
pengiriman	0.98940	0.98940	0.98940	0.98940

The experimental results of the CNN and RNN models for sentiment classification are shown in Figures 15 and 16. The experimental results of the CNN model are known to predict positive sentiment with a prediction of positive = 0.95 and negative sentiment with a prediction of negative = 0.93. On the other hand, the RNN model can predict positive sentiment, which is predicted to be positive = 0.88, and negative sentiment is predicted to be negative = 0.93. The experimental results of CNN and RNN models for sentiment classification on each aspect are shown in Tables 8 and 9.

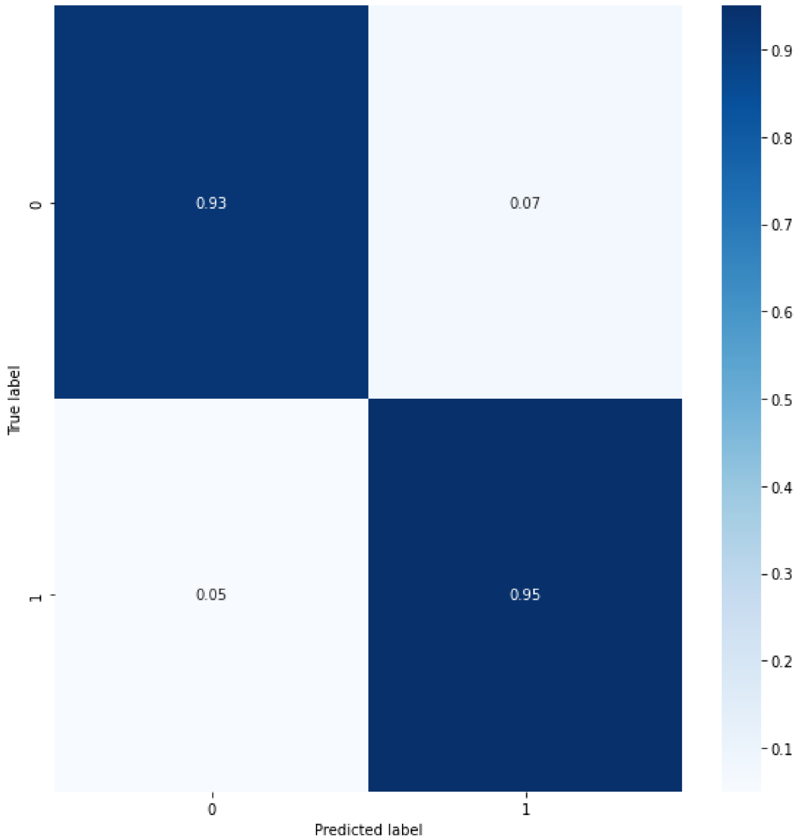

Figure 15. The result of the confusion matrix CNN.

Table 8. The experiment results of the CNN model in every aspect of sentiment classification.

Aspect	Sentiment	Count Sentiment	Accuracy	Precision	Recall	F1 Score
bahan	Positive	615	0.97236	0.97236	0.97236	0.97236
	Negative	673	0.92125	0.92125	0.92125	0.92125
kualitas	Positive	142	0.96479	0.96479	0.96479	0.96479
	Negative	97	0.91753	0.91753	0.91753	0.91753
pelayanan	Positive	248	0.96371	0.96371	0.96371	0.96371
	Negative	254	0.90158	0.90158	0.90158	0.90158
jahitan	Positive	101	0.98020	0.98020	0.98020	0.98020
	Negative	22	0.81818	0.81818	0.81818	0.81818
harga	Positive	176	0.99432	0.99432	0.99432	0.99432
	Negative	31	0.80645	0.80645	0.80645	0.80645
ukuran	Positive	127	0.91339	0.91339	0.91339	0.91339
	Negative	349	0.90831	0.90831	0.90831	0.90831
warna	Positive	112	0.72321	0.72321	0.72321	0.72321
	Negative	432	0.97917	0.97917	0.97917	0.97917
pengiriman	Positive	92	0.97826	0.97826	0.97826	0.97826
	Negative	191	0.97906	0.97906	0.97906	0.97906

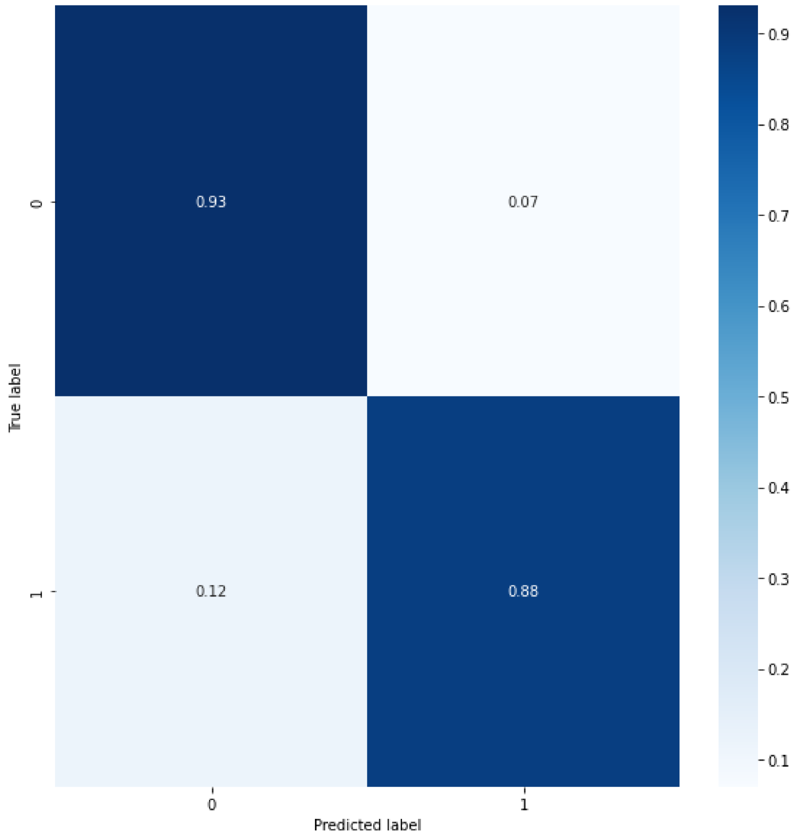

Figure 16. The result of the confusion matrix RNN.

Table 9. The experiment results of the RNN model in every aspect of sentiment classification.

Aspect	Sentiment	Count Sentiment	Accuracy	Precision	Recall	F1 Score
bahan	Positive	615	0.90569	0.90569	0.90569	0.90569
	Negative	673	0.92571	0.92571	0.92571	0.92571
kualitas	Positive	142	0.87324	0.87324	0.87324	0.87324
	Negative	97	0.92784	0.92784	0.92784	0.92784
pelayanan	Positive	248	0.87903	0.87903	0.87903	0.87903
	Negative	254	0.91732	0.91732	0.91732	0.91732
jahitan	Positive	101	0.95050	0.95050	0.95050	0.95050
	Negative	22	0.86364	0.86364	0.86364	0.86364
harga	Positive	176	0.94318	0.94318	0.94318	0.94318
	Negative	31	0.83871	0.83871	0.83871	0.83871
ukuran	Positive	127	0.79528	0.79528	0.79528	0.79528
	Negative	349	0.91118	0.91118	0.91118	0.91118
warna	Positive	112	0.65179	0.65179	0.65179	0.65179
	Negative	432	0.95139	0.95139	0.95139	0.95139
pengiriman	Positive	92	0.90217	0.90217	0.90217	0.90217
	Negative	191	0.95288	0.95288	0.95288	0.95288

In Tables 8 and 9, it can be seen that there is imbalanced data; actually, in the process, aspect classifications are not considered features. All data are considered equal, so the difference in the data amount is not affected. The process of grouping aspects is carried out without a training model but from the key phrases in the aspect sentences. So, the difference in the amount of data does not affect the classification process.

The comparison results of the GCN and GRN models for aspect classification are shown in Table 10. The comparison results of CNN and RNN models for sentiment classification are shown in Table 11. The comparison results show that the GRN model is superior to the GCN model for aspect classification with an F1 score of 0.97144, and the CNN model is excellent to the RNN model for sentiment classification with an F1 score of 0.94020. Based on the experimental results, the ABSA model built in this study can outperform the existing advanced models [39,40].

Table 10. The evaluation comparison of each model for aspect classification.

Model	Accuracy	Precision	Recall	F1 Score
GCN	0.96889	0.96889	0.96889	0.96889
GRN	0.97144	0.97144	0.97144	**0.97144**

Table 11. The evaluation comparison of each model for sentiment classification.

Model	Accuracy	Precision	Recall	F1 Score
CNN	0.94020	0.94020	0.94012	**0.94020**
RNN	0.90661	0.90661	0.90661	0.90661

Our ABSA model is tested using a combination of the best models that we have obtained in this study, testing the sample reviews "jahitan baik respon lama pengiriman cepat harga murah tapi ukuran kekecilan dan warna kusam", which in English is "good sewing long response fast delivery cheap price but the size is too small, and the color is dull". The result is shown in Figure 17.

```
Kalimat Input: jahitan baik respon lama pengiriman cepat harga murah tapi ukuran kekecilan dan warna
kusam
```

	aspect	opinion	sentiment	class_aspect
0	jahitan	baik	Positif	jahitan
1	respon	lama	Negatif	pelayanan
2	pengiriman	cepat	Positif	pengiriman
3	harga	murah	Positif	harga
4	ukuran	kekecilan	Negatif	ukuran
5	warna	kusam	Negatif	warna

Figure 17. The example-1 of using the ABSA model.

The ABSA results in Figure 17 obtained six aspects, with details:

1. Aspect: "jahitan" "sewing"; opinion: "baik" "good"; sentiment: "positif" "positive"; class_aspect: "jahitan" "sewing".
2. Aspect: "respon" "response"; opinion: "lama" "long"; sentiment: "negatif" "negative"; class_aspect: "pelayanan" "service".
3. Aspect: "pengiriman" "delivery"; opinion: "cepat" "fast"; sentiment: "positif" "positive"; class_aspect: "pengiriman" "delivery".
4. Aspect: "harga" "price"; opinion: "murah" "cheap"'; sentiment: "positif" "positive"; class_aspect: "harga" "price".
5. Aspect: "ukuran" "size"; opinion: "kekecilan" "too small"; sentiment: "negatif" "negative"; class_aspect: "ukuran" "size".
6. Aspect: "warna" "color"; opinion: "kusam" "dull"; sentiment: "negatif" "negative"; class_aspect: "warna" "color".

We tried another review example: "kualitas jelek kaos panas kurir lambat sekali tapi admin ramah", which in English is "bad quality hot t-shirts courier is very slow, but admin is friendly". The result is shown in Figure 18.

```
Kalimat Input: kualitas jelek kaos panas kurir lambat sekali tapi admin ramah
```

	aspect	opinion	sentiment	class_aspect
0	kualitas	jelek	Negatif	kualitas
1	kaos	panas	Negatif	bahan
2	kurir	lambat sekali	Negatif	pengiriman
3	admin	ramah	Positif	pelayanan

Figure 18. The example-2 of using ABSA model.

The ABSA results in Figure 18 obtained four aspects, with details:

1. Aspect: "kualitas" "quality"; opinion: "jelek" "bad"; sentiment: "negatif" "negative"; class_aspect: "kualitas" "quality".
2. Aspect: "kaos" "t-shirts"; opinion: "panas" "hot"; sentiment: "negatif" "negative"; class_aspect: "bahan" "material".
3. Aspect: "kurir" "courier"; opinion: "lambat sekali" "very slow"; sentiment: "negatif" "negative"; class_aspect: "pengiriman" "delivery".
4. Aspect: "admin" "admin"; opinion: "ramah" "friendly"; sentiment: "positif" "positive"; class_aspect: "pelayanan" "service".

Based on the results of using ABSA for the example above, the ABSA model we developed can detect aspect, opinion, and sentiment classification well.

The ABSA model that has been built automatically labels 11,270 unlabeled tuple graph data. The result is a total of 10,582 data detected as an aspect and 688 data detected as non-aspect, as shown in Table 12.

Table 12. The results of automatic labeling using the ABSA model.

Aspect	Positive	Negative	Count Aspect
bahan	2876	3419	6295
kualitas	100	199	299
jahitan	132	103	235
harga	84	441	525
ukuran	295	111	406
pelayanan	511	764	1275
warna	126	357	483
pengiriman	657	407	1064
Total aspects	4781	5801	10,582

The model that we have built has the weakness of not being able to detect if only one word is input; for example, the model cannot detect the word "barang" "item", and that is because the model we developed is in the form of aspect-based sentiment; our model is built using a dependency parser (https://nlp.stanford.edu/software/lex-parser.shtml (accessed on 2 December 2022) [6,38,39] that is used to detect relationships between words in a sentence so that there must be two or more words inputted for the model to be able to detect aspects and sentiments. In certain cases, there are weaknesses in the GRN model; for example, the word "tidak bagus" "not good" detects positive sentiments that should be negative. However, after we tested it on the GCN model, the word "tidak bagus" "not good" was detected with negative sentiment. Even though GRN's F1 score shows that it is superior to GCN, GRN has these deficiencies in this case. Apart from that, other shortcomings have been not being able to detect slang words, abbreviations, or non-standard words, for example, "brg jlk", which the model cannot detect. For example, with the abbreviation for the word "brg jelek" "bad brg" the model can still detect aspects and sentiments well. Even so, the model we have built is proven to be able to detect aspects and sentiments well with a minimum of two input words written by common words. Our trials show that our model is better than the previous sophisticated model [39,40].

5. Conclusions

The results of this study obtained the best Indonesian ABSA model. The GRN model is the best model for detecting aspects and opinions, with an F1 score of 0.97144. Meanwhile, the best model for sentiment classification was obtained using CNN with an F1 score of 0.94020. Based on the experimental results, the model developed in this study can outperform the best existing models [39,40] for ABSA in Indonesian and English. The ABSA model we have developed can automatically label 11,270 data, so we obtained 10,582 aspects and 688 non-aspects. For future research, we will develop this model for a wider domain and try to explore a graph-based approach for a wider domain.

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