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MULTI-LABEL TEXT CLASSIFICATION ON INDONESIAN USER REVIEWS USING SEMI-SUPERVISED GRAPH NEURAL NETWORKS

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Abstract. *Multi-label text classification is a basic and challenging job to develop Natural Language Processing (NLP). Compared to a single label, which works with the concept of having only one label in each sentence, it is easier to work with, while multi-label works by giving more than two labels to each sentence. Getting results from multiple labels precisely and accurately is a challenge. Data labeling is complicated and requires a lot of cost effort. This study developed a Semi-Supervised Graph Neural Network (SSGNN) model for multi-label text classification. A concept is implemented by utilizing a little labeled data and many unlabeled data. The data is obtained from scraping reviews of Indonesian marketplace users, 4,307 data are labeled manually, and 11,269 data are automatically labeled. The results of the evaluation of the SSGNN model obtained an accuracy value = 0.861250, precision = 0.918303, recall = 0.918664, F1 score = 0.918484. Result of multi-label text classification true aspect = 8,777 and false aspect = 2,492.*

Keywords: Multi-label text classification, Semi-supervised learning, Graph neural networks, Natural language processing, Indonesian user reviews

1. **Introduction.** Research in the field of Natural Language Processing (NLP) has increased [1,2]. Deep learning approaches have been widely applied to developing NLP [3,4]. An example of the application of NLP is used to analyze text data. Deep learning approaches have been used to analyze the complexity of text data [5,6]. Deep learning is developed using several models including supervised learning utilizing labeled data [7,8], unsupervised learning by utilizing unlabeled data [9,10], and semi-supervised learning by using a little labeled data and a lot of unlabeled data [11,12]. Data labeling is a significant concern in developing deep learning, but getting a lot of labeled data is very difficult and requires a lot of cost effort [13,14]. Therefore, the semi-supervised learning model can be applied to overcoming the problem of data labeling.

The semi-supervised learning model can be applied to overcoming the problem of limited labeled data by utilizing a large amount of unlabeled data [15,16]. User review data is obtained in unlabeled form and will be challenging in the labeling process. Implementing a semi-supervised model can be used to do a little labeling of data and perform an auto-label process for a lot of data. In data labeling, there is the term single label, which is on each piece of data, and multi-label is one piece of data with more than one label. As the name implies, multi-labels are very complex, so it requires challenges in the multi-label text classification process [17].

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Several methods in machine learning have been used to develop multi-label classification, including SVM, NB, K-Means [18], KNN [19], and CatBoost [20]. In addition, several methods in deep learning CNN, RNN [21] have been applied for multi-label classification. In [21], multi-label classification becomes a very important challenge and task in developing NLP and becomes a complex job compared to single-label text classification. Semi-supervised model is applied [22] for multi-label classification by utilizing a small amount of labeled data compared to the sum of all possible label combinations. However, the traditional approach only utilizes hidden states to explore contextual representations that may result in misclassification, or some may not be detected properly.

This study develops a Semi Supervised Graph Neural Network (SSGNN) model for multi-label text classification to minimize multi-label text misclassification. Currently, GNN has attracted the attention of researchers, such as in [23] applying GNN for text classification by adopting a similar network paradigm, namely using pre-training node insertion initialization and two-layer graph convolution. However, by implementing SS-GNN, the originally tabular data must be converted into a graph and represented in the form of a graph. This will be a challenge and requires hard work to be carried out in this research.

Novelty in this research is developing a semi-supervised graph neural network model for multi-label text classification by utilizing a little labeled data and utilizing a lot of unlabeled data sourced from scrapping reviews of Indonesian marketplace users. This paper is summarized as follows. Section 2 reviews some related work. An overall framework for the proposed method is provided in Section 3. The results and discussion are presented in Section 4 and Section 5 presents research conclusions with several further research perspectives.

2. **Related Work.** This research focuses on multi-label text classification by utilizing little labeled data and lots of unlabeled data. Multi-label text classification becomes a challenging basic task and very difficult to do in many real-world applications. [24] developed a Hierarchical Cognitive Structure Learning Model (HCSM) for Hierarchical Multi-Label Text Classification (HMLTC). In developing the HCSM model, there are Attentional Ordered Recurrent Neural Networks (AORNN) and Hierarchical Bidirectional Capsule (HBiCaps).

Multi-label text classification has been presented in [25], utilizing KNN to take several neighboring samples and add them to the model output with labels. The multi-label contrastive learning objective is designed to make the model aware of the KNN classification process and improve the quality of the neighbors taken during inference. There are two datasets used (AAPD and RCV1-V2). The results show that the developed model can bring consistent and significant performance improvements to several MLTCs, including advanced pre-training and non-pre-training.

A Label-specific Dual Graph Neural network (LDGN) has been proposed in [26], used to overcome the difficulty of distinguishing labels from representations of the same document for different labels. In addition, exploring high-level interactions between elements can help to predict tail labels. Utilizing three datasets (AAPD, EUR-Lex, and RCV1) shows that LDGN significantly outperforms the latest models and achieves better performance with respect to tail labels.

3. **Method.** The proposed model is Semi-Supervised Graph Neural Networks (SSGNN). Semi-supervised is designed by utilizing a little labeled data and a lot of unlabeled data. At the same time, graph neural networks are designed to represent the relationship between words in a sentence in the form of a graph by utilizing the theory of neural networks that has been widely studied. Figure 1 shows the steps of the proposed model.

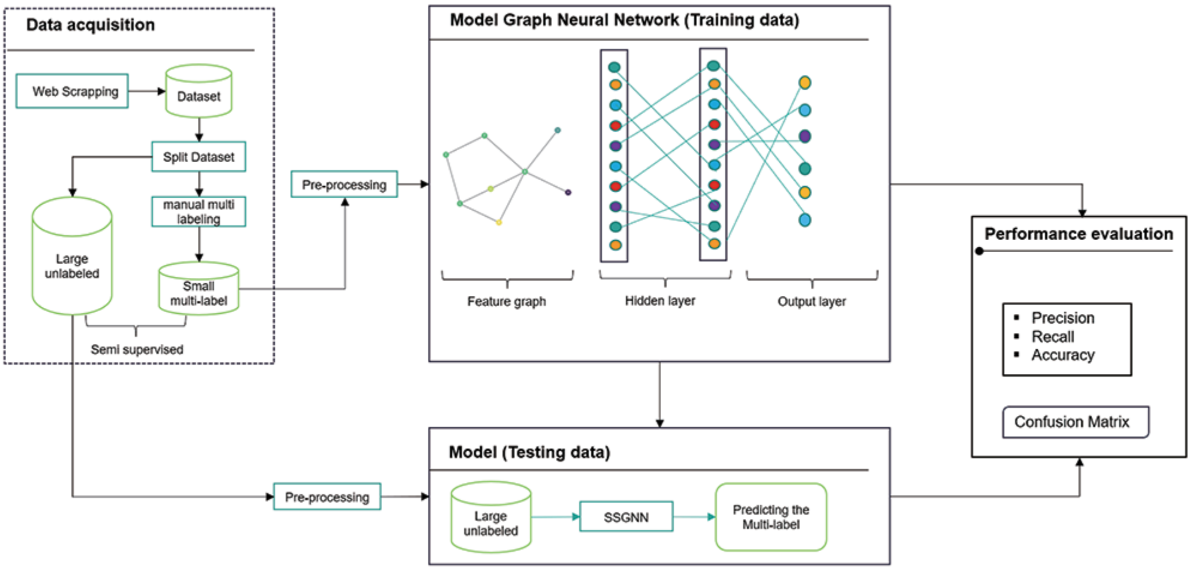


FIGURE 1. The overall framework for the proposed method

3.1. **Data acquisition.** This research utilizes the review data of Indonesian marketplace users obtained by scrapping data. The scrapping technique utilizes the chrome extension web scraper[1] tool. By utilizing the clicked element and the text element, a review sentence for the men's t-shirt product is obtained on the Indonesian marketplace platform. The results of scrapping obtained 15,240 data; data separation was carried out with details of 3,896 data used for the manual labeling process. The remaining 11,344 data are used in multi-label text classification automatically.

To simplify the data labeling process, you can take advantage of sentence extraction with the dependency tree approach in Stanford Dependencies[2]. The syntactic dependency relationship [27,28] can be calculated as in (1), (2), and (3).

$$DT\left(v_i^s, v_j^s\right) = \frac{1}{m-1} \sum_{s \neq j}^{m-1} d(i,k|j) \tag{1}$$

$$d(i,k|j) = C(i,k) - PC(i,k|j) \tag{2}$$

$$PC(i,k|j) = \frac{C(i,k) - C(i,j)C(k,j)}{\sqrt{\left[1 - C^2(i,j)\right]\left[1 - C^2(k,j)\right]}} \tag{3}$$

where $DT\left(v_i^s, v_j^s\right)$ is the syntactic dependency relationship between the nodes v_i^s, v_j^s in the dependency tree. This avoids the trivial case of the node j appearing to strongly affect the correlation $C(i,k)$, mainly because $C(i,j)$, $C(i,k)$ and $C(j,k)$ have small values. $PC(i,k|j)$ is a statistical measure indicating how a third node affects the correlation between two other nodes, where $C(i,j)$, $C(i,k)$ and $C(j,k)$ are the node correlations.

By utilizing the Indonesian language stanza[3] library, it is easier to extract sentences and get a syntax-based graph. After extracting the sentences, the labeling process can be carried out. An example of data labeling is shown in Table 1.

3.2. **Preprocessing.** Preprocessing is used to clean and prepare text [29,30]. In this study, the preprocessing stages used include (a) case folding is used to change all text in lowercase so that it is easy to process, (b) tokenization, which is used to remove

[1]https://chrome.google.com/webstore/detail/web-scraper-free-web-scra/jnhgnonknehpejjnehehllklipl mbmhn?hl=en

[2]https://nlp.stanford.edu/software/stanford-dependencies.html

[3]https://stanfordnlp.github.io/stanza/index.html

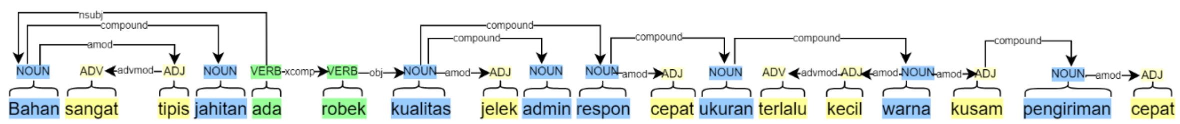
Table 1. The example of labeled data

Review	Aspect	Opinion	True tuple	Sentiment	Class aspect
bagus bahan adem jahit rapih (*nice, cool material, neat sewing*)	bahan *material*	adem *cool*	1	1	bahan
bagus bahan adem jahit rapih (*nice, cool material, neat sewing*)	jahit *sewing*	rapih *neat*	1	1	jahitan
barang bagus seller responsip kirim cepat (*good item, responsive seller, fast delivery*)	barang *item*	bagus *good*	1	1	bahan
barang bagus seller responsip kirim cepat (*good item, responsive seller, fast delivery*)	barang seller *seller's item*	responsip *responsive*	1	1	pelayanan

Description:
True tuple: 1 = there are aspects
0 = there is no aspect
Sentiment: 1 = positive
−1 = negative
0 = no sentiment
Class aspect: material (*bahan*), size (*ukuran*), color (*warna*), sewing (*jahitan*), quality (*kualitas*), price (*harga*), delivery (*pengiriman*), service (*pelayanan*).

punctuation marks, emoticons, tags, and numbers to produce good words, (c) stop-word removal is a process used to remove words that often appear but have no important meaning, and (d) stemming is the process of removing affixes in sentences to get the root word.

3.3. **Model semi-supervised graph neural networks.** In developing the model, the dependency tree and syntax-based graph approaches are used. Figure 2 shows dependency



Adjacency Matrix

	bahan	sangat	tipis	jahitan	ada	robek	kualitas	jelek	admin	respon	cepat	ukuran	terlalu	kecil	warna	kusam	pengiriman	cepat
bahan	0	0	amod	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
sangat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
tipis	0	advmod	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
jahitan	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
ada	nsubj	0	0	nsubj	0	xcomp	0	0	0	0	0	0	0	0	0	0	0	0
robek	0	0	0	0	0	0	obj	0	0	0	0	0	0	0	0	0	0	0
kualitas	0	0	0	0	0	0	0	amod	compound	0	0	compound	0	0	0	0	0	0
jelek	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
admin	0	0	0	0	0	0	0	0	0	compound	0	0	0	0	0	0	0	0
respon	0	0	0	0	0	0	0	0	0	0	amod	0	0	0	0	0	0	0
cepat	0	0	0	0	0	0	0	0	0	cc	0	0	0	0	0	0	0	0
ukuran	0	0	0	0	0	0	0	0	0	0	0	0	0	amod	0	0	0	0
terlalu	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
kecil	0	0	0	0	0	0	0	0	0	0	0	0	advmod	0	obj	0	0	0
warna	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	amod	compound	0
kusam	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
pengiriman	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	amod
cepat	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Figure 2. The example of the result of dependency tree and the adjacency matrix of the syntax-based graph

tree and adjacency matrix of syntax-based graph for review "Bahan sangat tipis jahitan ada robek kualitas jelek admin respon cepat ukuran terlalu kecil warna kusam pengiriman cepat", in English "The material is very thin, the stitches have torn, poor quality, admin fast response, size is too small, color is dull, fast delivery".

By utilizing the networkx[4] library, we can visualize a sentence extraction data graph in the form of an adjacency matrix from a syntax-based graph, as shown in Figure 3.

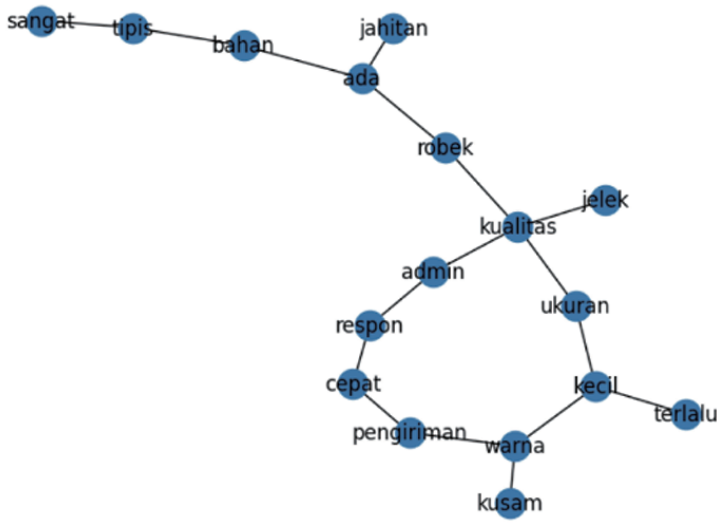


FIGURE 3. The example of graph networks

A syntax-based graph [28] is denoted by $G^s = (V^s, E^s, A^s)$, where V^s is a node that corresponds to the words in the sentence, E^s are the edges that connect between nodes, and A^s is a syntax-based adjacency matrix that represents a syntactic dependency relationship between nodes. The elements of the adjacency matrix A^s are determined as follows:

$$A_{ij}^s = \begin{cases} DT\left(v_i^s, v_j^s\right), & \text{if } v_i^s, v_j^s \in W \wedge v_i^s \neq v_j^s \\ 1, & \text{if } v_i^s, v_j^s \in W \wedge v_i^s = v_j^s \\ 0, & \text{otherwise} \end{cases} \tag{4}$$

where $DT\left(v_i^s, v_j^s\right)$ is the syntactic dependency relationship between the nodes v_i^s, v_j^s in the dependency tree.

The SSGNN architecture used in this study is shown in Figure 4. In this study using a sequential model with 3 layers, the 1st layer uses 7 neurons with sigmoid activation, the 2nd layer uses 24 neurons with sigmoid activation, then there is a dropout layer (0.2) to avoid overfitting, and the 3rd layer contains 1 neuron using sigmoid activation.

3.4. **Evaluation.** To evaluate the performance of the model, use confusion matrix [31] as in (5), (6), (7), and (8).

$$\text{Accuracy} = \frac{(\text{TP} + \text{TN})}{(\text{TP} + \text{FN} + \text{TN} + \text{FP})} \tag{5}$$

$$\text{Precision} = \frac{\text{TP}}{(\text{TP} + \text{FP})} \tag{6}$$

$$\text{Recall} = \frac{\text{TP}}{(\text{TP} + \text{FN})} \tag{7}$$

$$\text{F1 score} = 2 * \frac{\text{Recall} * \text{Precision}}{\text{Recall} + \text{Precision}} \tag{8}$$

[4]https://networkx.org/documentation/stable/

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

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense (Dense)               (None, 7)                 56

 dense_1 (Dense)             (None, 24)                192

 dropout (Dropout)           (None, 24)                0

 dense_2 (Dense)             (None, 1)                 25

=================================================================
Total params: 273
Trainable params: 273
Non-trainable params: 0
_________________________________________________________________
```

FIGURE 4. SSGNN architecture

4. **Results and Discussion.** The multi-label text labeling process on 3,894 data through preprocessing and sentence extraction obtained 4,307 data. After labeling the data, the results are as shown in Table 2.

TABLE 2. The statistics of datasets

Aspect	**True**	**False**	**Total**
bahan	1,288	3	1,291
kualitas	239	1	240
pelayanan	502	1	503
jahitan	123	0	123
harga	207	0	207
ukuran	476	3	479
warna	544	3	547
pengiriman	283	0	283
non-aspek	0	634	634

Based on 4,307 data that has been labeled by grouping it into 8 aspects as in Table 2, the details of aspects are obtained as material (*bahan*) = 1,291, size (*ukuran*) = 479, color (*warna*) = 547, sewing (*jahitan*) = 123, quality (*kualitas*) = 240, price (*harga*) = 207, delivery (*pengiriman*) = 283, service (*pelayanan*) = 503.

In the material aspect, there are 1,291 aspects that have been successfully extracted, labeled as 1,288 aspect as true and 3 aspect as false. In the quality aspect, 240 aspects have been successfully extracted, 239 aspects have been labeled as true, and 1 aspect as false. In the service aspect, there are 503 aspects that have been successfully extracted, 502 aspects have been labeled as true, and 1 aspect as false. In the sewing aspect, there are 123 aspects that have been successfully extracted, 123 aspects have been labeled as correct. In the price aspect, there are 207 aspects that have been successfully extracted, 207 have been labeled as correct. In the size aspect, there are 479 aspects that have been successfully extracted, 476 aspects have been labeled as true, and 3 aspects as false. In the color aspect, there are 547 aspects that have been successfully extracted, 544 aspects have been labeled as true, and 3 aspects as false. In the delivery aspect, 283 aspects have been successfully extracted, 283 aspects have been labeled as correct. There are 634 extracted data that have been labeled as no aspect.

The results of the development of the SSGNN model by utilizing 4,307 data as training data obtained the results of evaluating the performance of the model performance with the confusion matrix as shown in Figure 5. The results of the confusion matrix model of SSGNN are known to be true aspects predicted true aspect = 0.92, false aspect predicted false aspect = 0.52, true aspect predicted false aspect = 0.08, and false aspect predicted true aspect = 0.48.

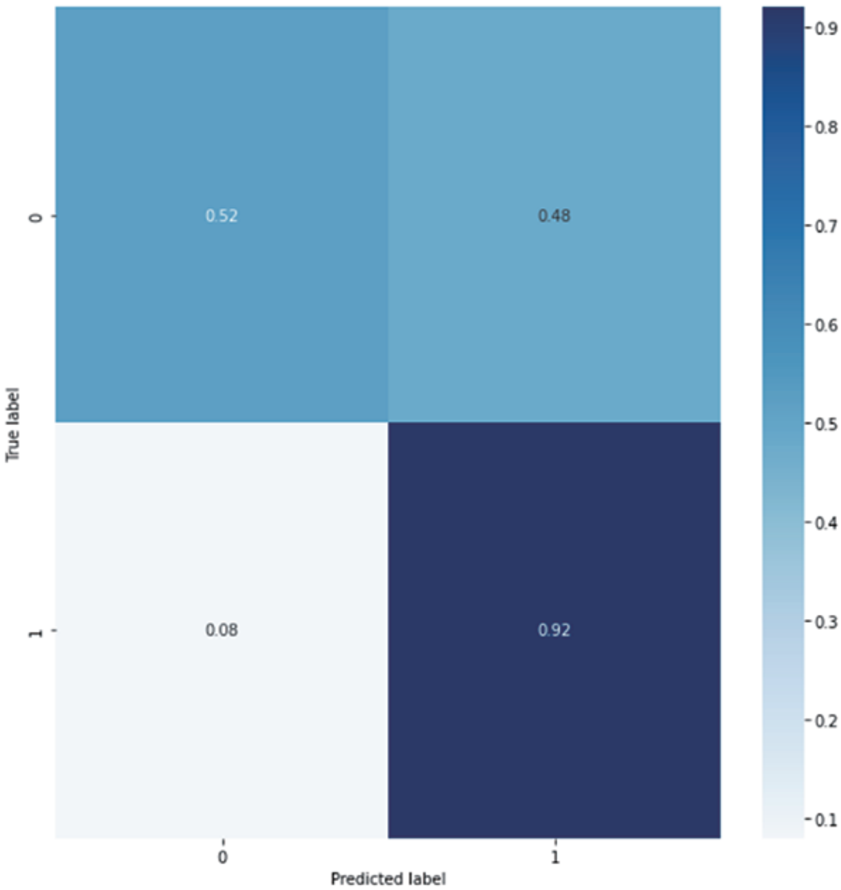


FIGURE 5. The result of the confusion matrix SSGNN

The results of the calculation of the accuracy of the SSGNN model, as shown in Figure 6 obtained accuracy = 0.86 and loss = 0.14. In Table 3, it is known that the overall model performance evaluation results obtained an accuracy value = 0.861250, precision = 0.918303, recall = 0.918664, F1 score = 0.918484.

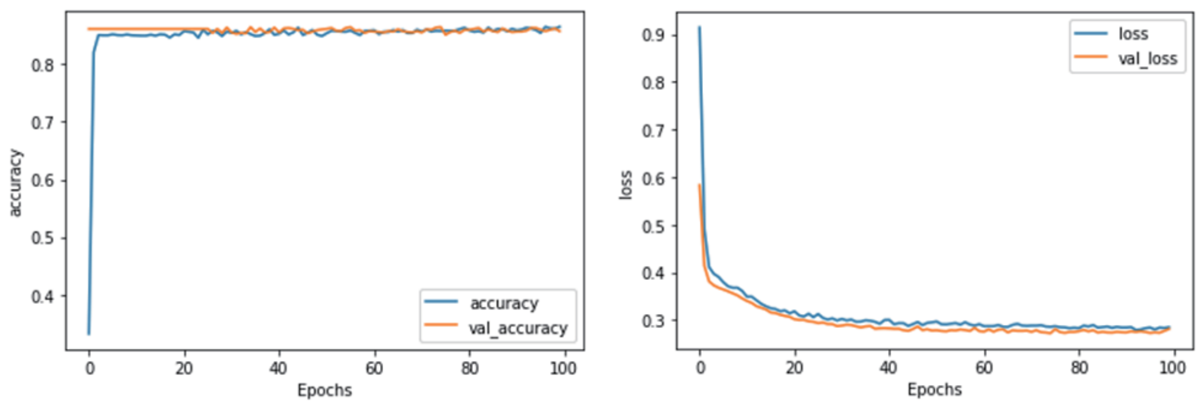


FIGURE 6. The data training process using SSGNN

TABLE 3. The results of the performance evaluation SSGNN model

Model	Accuracy	Precision	Recall	F1 score
SSGNN	0.861250	0.918303	0.918664	0.918484

In Table 4, it is known that the color aspect has the highest value at accuracy = 0.990792, precision = 0.994444, F1 score = 0.995366. The highest recall value is found in the sewing, price, and delivery aspect, with a recall value = 1.000000.

TABLE 4. The results of the performance evaluation SSGNN model based on the aspect

Aspect	Accuracy	Precision	Recall	F1 score
bahan	0.979070	0.981352	0.997630	0.989424
kualitas	0.966527	0.970588	0.995690	0.982979
pelayanan	0.952286	0.954183	0.997917	0.975560
jahitan	0.918699	0.918699	**1.000000**	0.957627
harga	0.990338	0.990338	**1.000000**	0.995146
ukuran	0.981053	0.987288	0.993603	0.990436
warna	**0.990792**	**0.994444**	0.996289	**0.995366**
pengiriman	0.858156	0.858156	**1.000000**	0.923664
non-aspek	0.189542	0.000000	0.000000	0.000000

After preprocessing 11,343 data obtained 11,269 data, the SSGNN model can label 11,269 data automatically. The result is 8,777 true aspects and 2,492 false aspects, with details as shown in Table 5.

TABLE 5. The results of text multi-label classification

Aspect	Total
bahan	4,931
pengiriman	1,062
pelayanan	1,001
harga	517
warna	438
ukuran	330
kualitas	277
jahitan	221
Total	8,777

In Table 5, it is known that the results of text multi-label classification for 11,269 data obtained material aspect = 4,931, delivery = 1,062, service = 1,001, price = 517, color = 438, size = 330, quality = 277, sewing = 221, with a total true aspect = 8,777 and false aspect = 2,492.

5. **Conclusions.** In this research, the chrome extension web scraper was used to obtain review data from Indonesian marketplace users. The results obtained were 15,237 data. Separated 3,894 data labeled manually and 11,343 data labeled automatically. The results of the development of the SSGNN model obtained an accuracy value = 0.861250, precision = 0.918303, recall = 0.918664, F1 score = 0.918484. The SSGNN model can be used for text multi-label classification of 11,269 data with the results of true aspect = 8,777 and false aspect = 2,492. In future research, deep learning graph comparisons will be carried out for the datasets that have been obtained in this research, and a model will be developed to improve aspect-based sentiment analysis.

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