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Multi-document summarization for patent documents based on generative adversarial network

Sunhye Kim, Byungun Yoon *

Department of Industrial & Systems Engineering, School of Engineering, Dongguk University, 3-26, Pil-dong 3ga, Chung-gu, Seoul 100-715, South Korea

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ABSTRACT

Given the exponential growth of patent documents, automatic patent summarization methods to facilitate the patent analysis process are in strong demand. Recently, the development of natural language processing (NLP), text-mining, and deep learning has greatly improved the performance of text summarization models for general documents. However, existing models cannot be successfully applied to patent documents, because patent documents describing an inventive technology and using domain-specific words have many differences from general documents. To address this challenge, we propose in this study a multi-patent summarization approach based on deep learning to generate an abstractive summarization considering the characteristics of a patent. Single patent summarization and multi-patent summarization were performed through a patent-specific feature extraction process, a summarization model based on generative adversarial network (GAN), and an inference process using topic modeling. The proposed model was verified by applying it to a patent in the drone technology field. In consequence, the proposed model performed better than existing deep learning summarization models. The proposed approach enables high-quality information summary for a large number of patent documents, which can be used by R&D researchers and decision-makers. In addition, it can provide a guideline for deep learning research using patent data.

1. Introduction

Patent documents contain detailed information about the technology and scope of the exclusive rights granted to the patentee. Some 71 % of technology published in patent literature is not published in other technical literature, such as scientific papers or reports, while 75 % of new scientific and technical knowledge appears only in patent specifications (Grayson, 1983; Straus, 1997). As such, patent claims have very rich technical value. They contain information that must be analyzed for R&D management and technology economy analysis (Yoon & Park, 2004). Many companies and research institutes collect, analyze, and summarize information about technology on their own through an expert-based patent review process. Recently, with the shortening of the technology development cycle and rapid social change, the number of patent documents is increasing exponentially. As a result, the patent summarization process performed by human is becoming increasingly difficult, and the demand for patent processing aids is increasing (Brügmann et al., 2015). Although studies of patent document summarization methods considering characteristics of patents are being conducted, most studies tend to provide information about technology by focusing on visualization. However, summaries in the form of graphs or figures do not sufficiently express the rich information contained in the text of the patent. With the development of natural language processing (NLP), text-mining, and deep learning, the performances of text summarization models for general documents have greatly improved. In particular, deep learning-based models, such as models using Generative Adversarial Network (GAN), show good performances (El-Kassas, Salama, Rafea, & Mohamed, 2021; Liu et al., 2018; Liu & Lapata, 2019; Rekabdar, Mousas, & Gupta, 2019; Vo, 2021; Yang et al., 2020; Zhuang & Zhang, 2019). However, it is difficult to apply a general summary algorithm, because patent documents, especially patent claims, have many differences from natural language constituting general documents (Sheremetyeva, 2013). Since a patent is a document that describes an inventive technology, domain-specific words are often used. In addition, the lengths of its sentences are very long (Kando, 2000). Moreover, it is written in technical and legal language with sentences providing dense information, making it difficult to summarize the patent (Sheremetyeva, 2014).

* Corresponding author.
E-mail address: postman3@dongguk.edu (B. Yoon).

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Studies that aim to generate textual patent summary can be divided into single patent document summarization (SPDS), and multi-patent document summarization (MPDS). SPDS studies focus on improving readability by simplifying patent claims known to have complicated structure, rather than summarizing patent information. Shinmori, Okumura, Marukawa, and Iwayama (2003) proposed a rule-based method for structuring a patent claim with a complex structure into a simple structure to make a readable summarization. Bouayad-Agha, Casamayor, Ferraro, and Wanner (2009) proposed a methodology for simplifying claims, breaking sentences into short sentences, and removing or replacing parts of sentences according to rule-based summary criteria to create summary sentences. Trappey, Trappey, and Wu (2009) proposed an ontology TF−IDF (term frequency – inverse document frequency)-based methodology for automatically and systematically extracting information from patent documents to enhance knowledge sharing and collaboration among R&D team members. In addition, patent document summary models incorporating TRIZ (TIPS, theory of solving inventive problem), a creative problem-solving theory based on patent data analysis, have been proposed (Altshuller, Al'tov, & Altov, 1996). Guarino, Samet, Nafi, and Cavallucci (2020) defined contradiction and inventive design method (IDM) information (concepts derived from TRIZ) as core information in patents, and proposed a model that can automatically extract sentences, including contradictions and IDMs. In particular, they proposed a model to extract the contradiction related to the initial problem of patents, and the contradiction related to the shortcomings of existing technical solutions, using a Bert-based classification model. In addition, the model proposed by Berduygina and Cavallucci (2020) aims to extract a sentence including Inventive Design Methodology (IDM) information derived from a pattern using linguistic and statistical methods after structuring a patent claim. However, these SPDS studies have limitations, in that they depend on language rules and grammar. Rule-based methodologies with many manual processes are mainly used. Furthermore, since most of the rules depend on a domain, they could only be applied within a specific field. Since SPDS summarizes only one patent, it cannot provide comprehensive information on the corresponding technology domain. Therefore, models for summarizing several patent documents belonging to a technology domain have also been proposed.

In general, multi-document summarization (MDS) is considered a more difficult task than single document summarization (SDS). MDS tends to produce summaries with greater redundancy than SDS, because documents with similar subjects contain a lot of overlapping information. The compression rate of MDS also tends to be small (Goldstein, Mittal, Carbonell, & Kantrowitz, 2000; Ou, Khoo, & Goh, 2008). From a data set point of view, a lack of human-written summaries is another factor that makes MDS difficult. Although many SDS datasets exist, MDS datasets generally do not exist. In the case of a patent, the title or abstract of the patent can be used for SPDS. However, there is no data available from the point of view of the MPDS. Souza, Santos, Meireles, and Almeida (2019) proposed a LexRank-based methodology that can automatically summarize abstracts and descriptions of patent documents to help patent examiners create patent sub-classes and name corresponding classes. Trappey, Trappey, Wu, and Wang (2020) proposed an encoder–decoder-based deep learning application summary model. Girthana and Swamynathan (2020) proposed a summary model using a Boltzmann machine. However, these MPDS models also have limitations. Although these proposed models can generate extractive summaries, information cannot be summarized well. This is because rather than reconstructing new sentences, summaries are generated by selecting existing sentences or phrases. A method of presenting a summary for each cluster by creating clusters from a patent set consisting of several patents has mainly been adopted. However, by using the cluster as the same classification as the previously defined patent classification code like international patent classification (IPC) or cooperative patent classification (CPC), a summary reflecting the technical point of view of the text information of the patent dataset could not be achieved. In addition, these MPDS methods did not consider the structure of the patent proposed by SPDS studies.

To address the above challenge, we propose a multi-patent summarization methodology in this study to generate an abstractive summarization considering the characteristics of a patent. This study used the Generative Adversarial Network (GAN) algorithm as one of the deep learning models to enable abstractive summarization (Zhang, Gan, & Carin, 2016). By composing input data considering the characteristics of patents, the deep learning model could learn important technical information contained in patent documents. We also propose a two-level summarization architecture for the MPDS. The final result is presented at two levels. Level 1 aims to present a summary at a single patent level. Level 2 aims to present a summary at multiple patent levels by topic. The rest of this paper is structured as follows: Section 2 reviews the existing text summarization models and GAN models, then Section 3 proposes a patent summarization model and research framework. Section 4 presents exemplary results for drone technology, while Section 5 provides validation and discussion. Section 6 discusses limitations of this study, and indicates future research directions.

2. Background

2.1. Text summarization models

In addition to SDS and MDS reviewed in the introduction, document summarization can be divided into extractive summarization and abstractive summarization. Extractive summarization aims to generate a summary by selecting and extracting core sentences among the sentences existing in the source document. For this, various approaches have been proposed, including statistics-based approaches, topic-based approaches, graph-based approaches, and machine learning-based approaches (Gambhir & Gupta, 2017). First, statistics-based approaches extract important sentences using statistical features, such as the position of the sentence in the document, the frequency of word occurrence, and the length of the sentence (Ko & Seo, 2008; McCargar, 2004). Topic-based approaches define a topic that appears in common in a set of documents, and then summarize the main content, that is, a topic that appears in a specific document based on this (Lin & Hovy, 2000). Graph-based approaches analyze the document as a network. A sentence or word is regarded as a single node, and the relationship between two nodes (whether they appear at the same time, or whether they are semantically similar, etc.) is defined as an arc. A representative model of a graph-based approach is LexRank, which selects important sentences through centrality analysis or random walk analysis for the created network (Erkan & Radev, 2004; Thakkar, Dharaskar, & Chandak, 2010). Recently, machine learning based approaches have been suggested that when a document is entered, can train a model to generate a summary, using training data consisting of a pair of documents and summaries (Miller, 2019; Sinha, Yadav, & Gahlot, 2018).

Words and sentences constituting the summary generated by the extractive methodology have the limitation that they are the same words and sentences existing in the source document. On the other hand, the summary generated by the abstractive methodology consists of words and sentences that are different from those existing in the source training document. The abstractive summary also provides a document composed of contents of the source document. However, the summary can be reinterpreted and reconstructed. It can be expressed with completely different words and sentences. For abstractive summarization, an advanced NLP processing technique that can better express the semantics and syntactic information of a sentence is needed. Many existing NLP models learn the arrangement of words, and then generate word sequences based on learned word occurrence trends, there being the difficulty of considering the importance of rare words (Song, Huang, & Ruan, 2019). Since the abstractive summary method is a challenging and more complex task than the extractive summary method, studies proposing an abstractive summary model have been less actively conducted, than studies proposing an extractive summary model. Recently, with the development of deep learning, abstractive models have been actively proposed, with many models having encoder and decoder structures of the neural network. After learning features of the entire document sequence with an encoder, a sequence of summary sentences is generated with a decoder (Magdum & Rathi, 2021). Song et al. (2019) proposed a model that can consider both semantics and syntactic structure by using Long Short-Term Memory (LSTM) as an encoder, and Convolutional Neural Network (CNN) as a decoder. Zhang, Li, Wang, Fang, and Xiao (2019) suggested a convolutional seq2seq model, an encoder–decoder summarization model that applies a copying mechanism and a hierarchical attention mechanism to solve word sparsity. The model proposed in this study is an abstractive summary model of multi-patent documents. This study uses the seq2seq model, which has been widely used in these research fields.

2.2. Generative adversarial network (GAN) algorithm

GAN, a model first proposed by Goodfellow et al. (2014), shows strong performance in the computer vision and image generation fields (Radford, Metz, & Chintala, 2015). Unlike the existing single generative model, the GAN structure has a discriminator model that competes with the generative model, and learns. The generative model aims to generate fake data (G(z)) like the real one, by learning the distribution of the training data. The discriminator model aims to discriminate between real data (X) and generated fake data (G(z)) (Fig. 1). Through learning, the discriminator model can better discriminate against sophisticated fake data, and the generator can generate more sophisticated fake data with the goal of deceiving the discriminator model. Since the learning directions of these two models are opposite to each other, this learning structure is called adversarial learning.

Since GAN was designed to generate differentiable continuous data, it showed good performance in the image field. However, it did not show good performance in the discrete and sequential sentence generation field (Yu, Zhang, Wang, & Yu, 2017). If generated data are discrete, such as a sentence in word units, there is a problem that a 'more similar value' may not be an actual token. In addition, the discriminator of the existing GAN model cannot evaluate the result in the middle of the sequence. To solve this problem, models such as SeqGAN, LeakGAN, MaskGAN, and DP-GAN using reinforcement learning methods have been proposed (Fedus, Goodfellow, & Dai, 2018; Guo et al., 2018; Xu, Ren, Lin, & Sun, 2018; Yu et al., 2017). These models are trained by directly updating the generator using the stochastic policy of reinforcement learning. There are also models that consider the characteristics of discrete texts well through other learning methods, without using reinforcement learning (Zhang et al., 2016; Haidar & Rezagholizadeh, 2019). TextGAN makes it possible to better consider more discrete data by using moment-matching to learn both the results of the discriminator, and the similarity of learning features (Zhang et al., 2016). TextKD-GAN uses an LSTM encoder–decoder as a pre-training model based on teacher forcing learning (Haidar & Rezagholizadeh, 2019). In addition, many GAN-based models for more realistic text generation have been proposed.

Another application of GAN in the text field is abstractive text summarization. As mentioned earlier, abstractive text summarization is still a challenging field, and many studies are being conducted. The difficulty is that the generated summary must have a syntactically sensible sentence. At the same time, it must contain information of the original document. GAN has the advantage of being able to calculate the reward by evaluating the summary generated using different types of discriminators. This advantage enables learning that reflects the various conditions of a good summary mentioned above. Liu et al. (2018) proposed a text summarization GAN model with LSTM-based generator and binary classifier discriminator, and showed its effectiveness through experiments. Zhuang and Zhang (2019) proposed a model with a generator and two discriminators based on a hybrid pointer–generator network. The first discriminator evaluates the readability of the generated sentence, while the second discriminator evaluates the similarity between the full document and the summary. PGAN-ATSMT has been suggested for the purpose of generating syntactically correct summary sentences. It is composed of a seq2seq based generator with LSTM encoder and decoder and a language model discriminator (Yang et al., 2020). SGAN4AbSum uses BERT-GAN, a pretrained language model, as a generator and discriminator (Vo, 2021). As such, studies applying GAN have proposed summarization models with better performances through modification of the generator, discriminator, and learning method.

In this study, generator G takes the full text as input, and generates a summary. It also implements discriminator D as a text classifier that learns to classify generated summaries as machine or human-generated. Discriminator D tries to distinguish target summaries from summaries generated by generator G, whereas the purpose of training for generator G is to maximize the probability that D makes a mistake. Thus, this adversarial process can eventually train G to produce a plausible, high-quality abstractive summary.

3. Research framework

3.1. Basic concept

The proposed patent summarization framework consists of three steps. The first step is for patent feature extraction. This is a step of extracting learning features from a patent (Fig. 2A, Patent feature extraction). First, patent documents related to the defined technical field are collected. To learn in consideration of patent characteristics, the feature extraction process must be distinguished from other cases where plain texts are used. Features to be used in this study can be divided into commonly used features in the NLP field, and patent-specific features. As the next step, collected patents are pre-processed. Features are extracted, and then converted into the form of data that can be entered into the learning model. The second step is a learning stage for the patent summarization model. The generator and the discriminator of the GAN model structure training proceed in alternating periods (Fig. 2B, Summarization model training). In addition, label classifiers are trained to generate label data, so that additional information, along with text summaries, can be provided. In the third step, an inference model is constructed using the generator model trained in the patent summarization model's learning step (Fig. 2C, Patent summary generation). The inference model has two levels. The first level is the summary of a single patent. The second level adds topic modeling to generate a multi-patent document summary considering the topic.

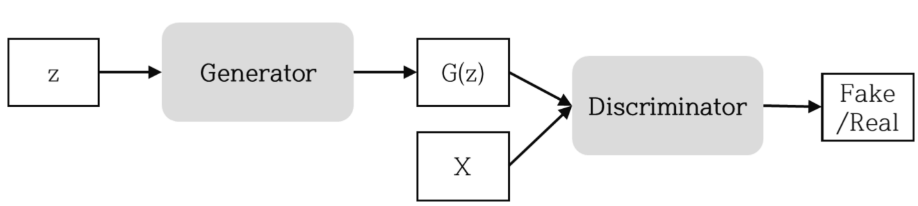

Fig. 1. GAN architecture.

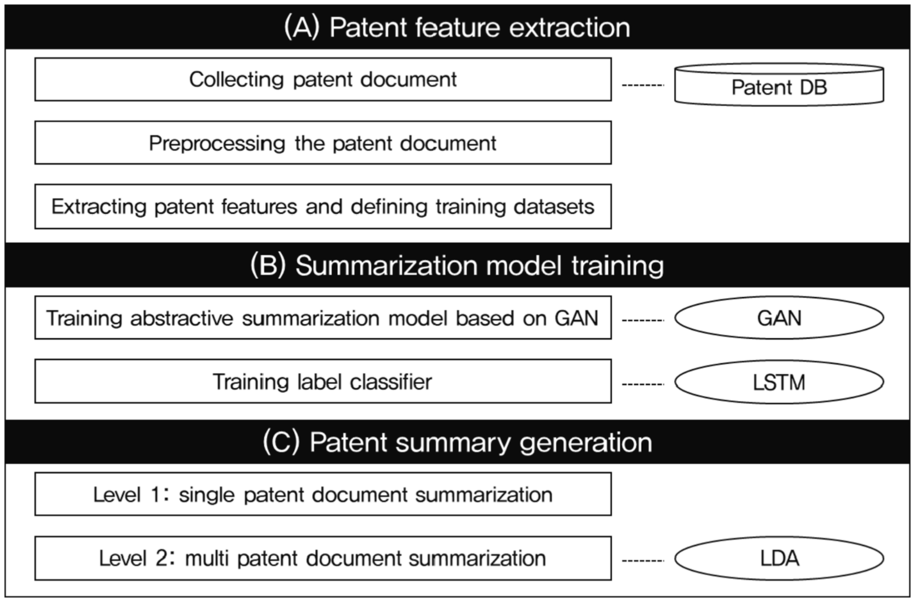

Fig. 2. Overall framework.

3.2. Detailed process

3.2.1. Patent feature extraction

In the patent feature extraction stage, patent documents are collected, features suitable for learning are extracted, and patents are converted into learning data. Compared to a general document containing plain text, the patent document has technical information and legal information. As the features used in general text learning, it is not possible to consider all the additional information of the patent. In this study, we intended to use both features commonly used in NLP, and features that are specialized for patents. Common features include word embedding, position information, and application time. The word embedding feature indicates the embedding vector of the word constituting the patent document. In general, researchers can use the embedding vector pre-trained with Word2Vec or Glove, or use it through the embedding layer within the model. Position information is information on the position of the word appearing in the sentence. Application time provides information on the time when the patent document is applied.

Patent-specific features additionally used in this study include TEMPEST class, subject–action–object (SAO) class, and problem/solution embedding. TEMPEST class and SAO class are features based on SAO structures used in the function analysis of TRIZ (Altshuller et al., 1996). The function analysis maps the system into an SAO structure to idealize the problem of the system's function. The SAO structure consists of a 'Subject', an 'Action', and an 'Object'. This is interpreted as a structure having a relationship between means (Subject) and purpose (Action–Object). If Action–Object (AO) describes a technical problem and Subject (S) indicates a solution, it can be interpreted as a relationship between the problem and the solution (Moehrle, Walter, Geritz, & Müller, 2005). Therefore, it can be used appropriately for patents, which are documents that describe solutions to specific technical problems. Many studies have conducted patent analysis using the SAO structure (Guo, Wang, Li, & Zhu, 2016; Roh, Jeong, & Yoon, 2017; Yoon & Magee, 2018). Previous studies applying TRIZ have tried to summarize patents by extracting sentences containing contradiction or IDM among the concepts of TRIZ. In other words, previous studies have tried to summarize patents in terms of creative inventions suggested by the analysis methodology of TRIZ. However, the framework proposed in this study uses features derived from the SAO structure of TRIZ as model training input, rather than focusing on contradiction or IDM, because it aims to summarize the overall contents of patent documents, and we believe that the GAN model can learn such inventive characteristics. In training the GAN model, the features derived from TRIZ are used at the same level as features of the existing NLP model. From this point of view, this study intends to use TEMPEST class and SAO class features, which are features based on the SAO structure, for patent-specific features. TEMPEST class is a feature that indicates where the action of the SAO structure belongs among five classes identified by the TEMPEST framework. TEMPEST used in this study is a framework used to analyze the contents of technical information in the patent from five viewpoints (*M, P, E, S,* and *T*). It aims to view technical contents from multiple viewpoints (Yoon, Park, & Jeong, 2016). Material (*M*) is a class that represents materials, ingredients, components, and so on. Personality (*P*) is a class that represents uses, characteristics, functions, and so on. Energy (*E*) represents power, light fixture, principle, and so on. Space (*S*) is a class representing structure, arrangement, element, device, mechanism, and so on. Time (*T*) represents a manufacturing method, control processing method, and so on. In this study, by using the definition of TEMPEST, action words belonging to each class are defined and used in a rule-based approach (Table 1). The SAO class is a feature indicating which part of the SAO structure the corresponding word belongs to. Since the S of the SAO structure mainly indicates a solution to a problem, it has a characteristic expressed as a noun phrase, such as the name of a specific technology or machine. A is mainly expressed as a verb or adjective phrase. It has the characteristic of indicating the problem to be

Table 1
TEMPEST word.

Tempest class	Word
Time	manufacture control process framework configure facilitate produce design implement
Energy	drive principle fundamental power impetus force stimulus momentum thrust propulsion apply rotate transfer insert affect effectuate convey perform
Material	material ingredient component constituent content contain incorporate
Personality	stabilizes vibrates intensify increase measure stabilize extended generate inhibit deliver utilize constrain preserve deflate equalize adjust
Space	include have composed comprise supply assemble consist organize build construct connect separate deploy

solved together with O expressed as a noun phrase. In this study, POS tagging is performed using the Stanford parser. The SAO structure is then extracted, and used based on the rule-based methodology proposed in the previous study (Klein & Manning, 2003). The last feature, problem/solution class, is a feature indicating whether the sentence in which the corresponding SAO structure appears is a part that explains the problem (SAO from the patent background), or the part that explains the solution (SAO from patent claims). A patent document describes an unprecedented solution to a certain technical challenge. Therefore, the problem to be solved and the solution are clearly defined in the document, and should be considered as important information in the model using patent data. Table 2 summarizes features to be used in this study.

Fig. 3 shows an example of using extracted features to configure input embedding. The input embedding is constructed by concatenating six features suggested for each word in the document. The example sentence is "A head mounted display including a display section that allows a user …". At this time, word embedding is generated as a vector of hidden size for each word constituting the sentence: Vec[A], Vec[head], Vec[mounted], Vec[display]. Position embedding is defined word-by-word in the order in which they appear: [A] is P1, [head] is P2, and so on. Applicant time is defined so that all words from the same document have the same application time label T1. TEMPEST class and SAO class are defined in the SAO structure unit. The phrase [head mounted display including a display section] of the example sentence can be structured as one SAO structure. At this time, the [head mounted display] phrase is the subject of the SAO structure, [including] is the action, and [display section] is the object. Since the corresponding SAO phrase has the verb [include] belonging to the space category of the TEMPEST class as action, all words belonging to the phrase have TEMs as the TEMPEST class. In addition, words [head], [mounted], and [display] are defined as the S class of SAO, while [including] is defined as A class, and [display] and [section] are defined as O class.

3.2.2. Patent summarization architecture

The proposed patent summary framework is largely composed of the summarization model based on GAN and label classifier (Fig. 4). The summarization model based on GAN is a model of the structure within which the generator and the discriminator compete. The generator is a model that generates summary sentences by inputting single patent text data and label data. It is composed of an encoder and a decoder. The discriminator is a model that receives the text data of summary sentences, and determines whether the corresponding sentence is a generated sentence or an actual sentence.

The generator is a transformer-based text summarization model. A generated summary text $\widehat{Y} = \{\widehat{y}_1, \widehat{y}_2, \widehat{y}_3, \cdots, \widehat{y}_M\}$ is generated by inputting the full text $X = \{x_1, x_2, x_3, \ldots, x_N\}$ defined in the patent feature extraction step into the model, and the target summary is $Y = \{y_1, y_2, y_3, \ldots, y_M\}$, where N is the number of words in the full text, and M is the number of words in the summary text. The transformer is constructed by stacking encoder blocks and decoder blocks. In this study, four blocks were stacked and used. The encoder block of the generator consists of an embedding layer, a multi-head attention layer, a first regularization layer, a feed forward layer, and a second regularization layer. When X is input into the encoder, the above layer operations are sequentially performed, and the encoder block output is calculated. At this time, the existing transformer model performs the positional encoding process to combine word embedding and position information where the word appeared. In this study, instead of the corresponding process, the process of concatenating the features extracted in the word embedding and feature extraction steps was performed. The decoder consists of a masked multi-head attention layer, a first regularization layer, a multi-head attention layer, a second regularization layer, a feed forward layer, and a third regularization layer. The word $\widehat{y}_{t-1}$ generated in the previous step is input into the first layer of the decoder, and the output of the encoder block is input into the multi-head attention layer of the decoder block. The decoder block output finally enters the dense layer, and generates the next word, $\widehat{y}_t$. The discriminator is a classification model consisting of one bi-LSTM layer. It receives the generated summary sentence $\widehat{Y}$ or the target summary sentence Y as input, and determines whether it is a real sentence or a generated sentence. The output of the discriminator is used as a reward to train the generator and discriminator.

The objective function of the discriminator is very similar to the objective function of vanilla GAN. The objective function of vanilla GAN is defined to have a maximum value when D(x) is 1 and D(G(z)) is 0 (Eq. (1)). D(x) is the result of inputting the target sentence $x \sim P_{tar}(x)$into the discriminator, and D(G(z)) is the result of inputting the sentence G(z) generated through the random vector $z \sim P_z(z)$into the discriminator. That is, the discriminator is trained to discriminate the target sentence, which is the real sentence, as the real sentence, and the generated sentence as the generated sentence. The discriminator objective function used in this study is defined to have a minimum value when $D_\varnothing(Y)$ is 1 and $D_\varnothing(\widehat{Y})$ is 0. At this time, $D_\varnothing(Y)$ is the result of inputting the target abstract sentence $Y\ P_{tar}$ into the discriminator, and $D_\varnothing(\widehat{Y})$ is the result of inputting the generated summary sentence $\widehat{Y}\ G_\theta$ into the discriminator (Eq. (2)). In other words, the discriminator is trained to discriminate the target abstract sentence as a real summary sentence, and the generated summary sentence as the generated sentence. Here, $\varnothing$ is a parameter of the discriminator, and θ is a parameter of the generator.

$$min_G max_D L(D,G) = E_{x\ P_{tar}(x)}[logD(x)] + E_{z\ P_z(z)}[\log(1-D(G(z)))] \tag{1}$$

$$min_\varnothing - E_{Y\ P_{tar}}[logD_\varnothing(Y)] - E_{\widehat{Y}\ G_\theta}[\log(1-D_\varnothing(\widehat{Y}))] \tag{2}$$

The generator's loss was defined using the sentence level reward and word level reward proposed in DP-GAN (Xu et al., 2018). Here, T is the number of generated summary sentences, y^t is the generated t-th summary sentence, M is the number of words constituting the sentence y^t, and y^t_m is the m-th word of the y^t sentence. The loss gradient of the generator is approximated as shown in Eq. (3), where γ is the discount rate. $R_{t,m}$ is a reward from y^t_m to y^t_M. It consists of a sentence level reward, and a word level reward (Eq. (4)). The sentence level reward $R(y^t)$ is defined as Eq. (5), and the word level reward $R(y^t_m)$ is defined as Eq. (6):

$$\nabla_\theta J(\theta) \cong \sum_{t=1}^{T}\sum_{m=1}^{M}\gamma^{m-1}R_{t,m}\nabla_\theta logG_\theta\left(y^t_m|y^t_{<m}\right) \tag{3}$$

$$R_{t,m} = \sum\nolimits_{i=m}^{M}\gamma^{m-1}R(y^t)R(y^t_m) \tag{4}$$

$$R(y^t) = -\frac{1}{M}\sum\nolimits_{i=m}^{M}logD_\varnothing\left(y^t_m|y^t_{<m}\right) \tag{5}$$

$$R(y^t_m) = -logD_\varnothing\left(y^t_m|y^t_{<m}\right) \tag{6}$$

Table 2
Definition of Features.

	Feature	Definition
General feature	Word embedding	Embedding vector of the word
	Position information	Position information of the word in the sentence
	Application Time	Application time information of the patent document
Patent specific feature	TEMPEST class	TEMPEST class of the Action in SAO structure to which the word belongs
	SAO class	A class indicating which part of the SAO structure it belongs to
	Problem/ Solution class	A class indicating whether the sentence with the corresponding SAO structure is the part that explains the Problem (SAO from the patent background), or the part that explains the solution (SAO from the patent claims)

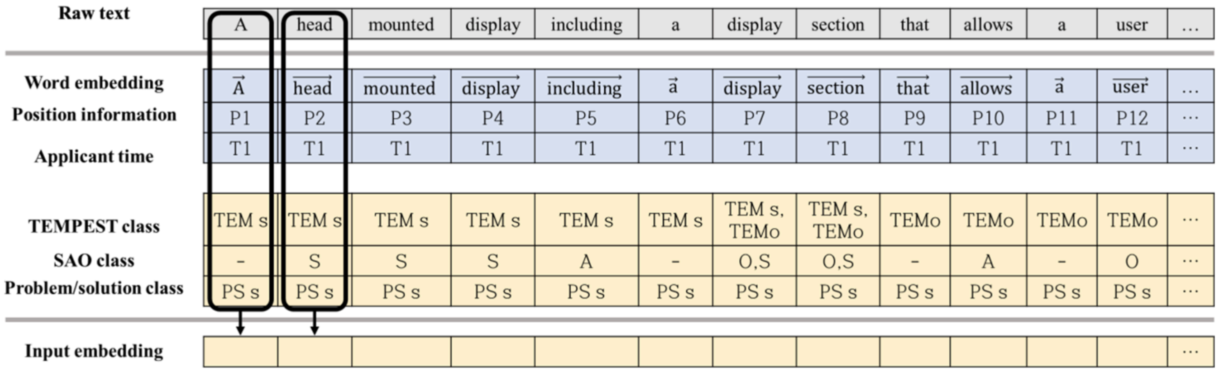

Fig. 3. Input embedding.

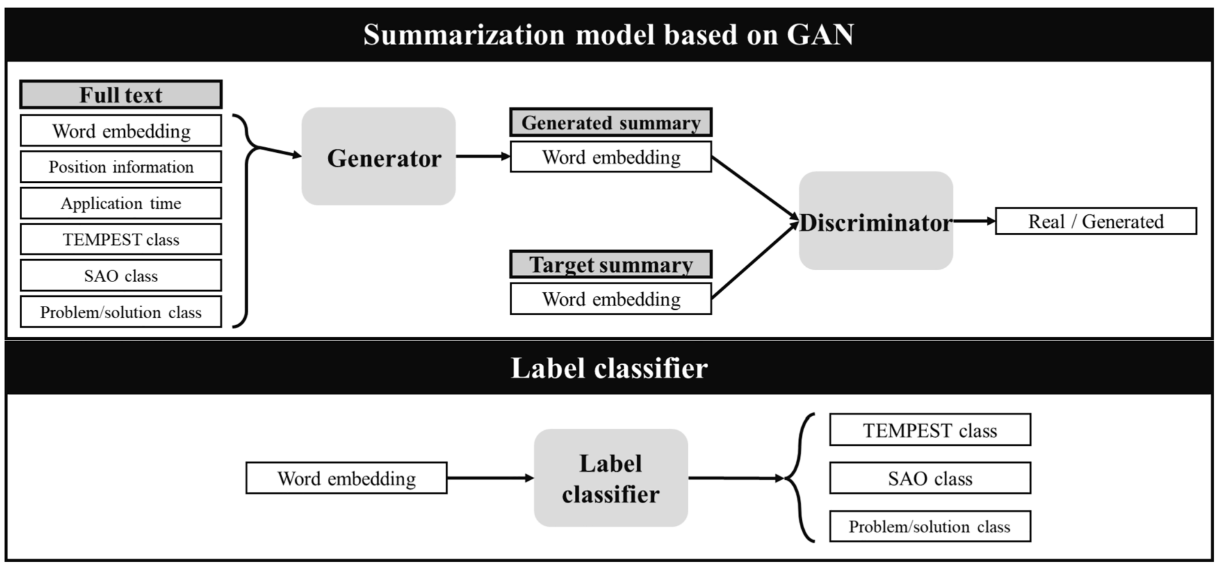

Fig. 4. The proposed model architecture.

Finally, the label classifier is a classification model composed of one bi-LSTM layer. It is used in the inference step. The label classifier classifies TEMPEST class, SAO class, and problem/solution class for each word of the full patent text.

3.2.3. Inference

In the inference stage, the summary sentence of a single patent and the TEMPEST class, SAO class, and problem/solution class of the words constituting the summary sentence are generated, and MPDS is generated for each topic (Fig. 5). In this case, generating an SPDS is at Level 1, and generating a summary for MPDS is at Level 2. For this inference, we used the generator and label classifier trained in patent summary model training, and additionally performed topic modeling.

A summary of a single patent is generated at Level 1. With the full text and label data of a single patent as input, the generator generates a summary sentence. The label classifier generates labels for the generated summary. In this case, the generated label can be used for a richer interpretation of a single patent summary sentence. In other words, when the full text word embedding of a patent tokenized in word units is input into the generator, summary text word embedding tokenized in word units is output. By inputting the summary text word embedding into the label classifier, the TEMPEST class, SAO class, and problem/solution class are derived for each word token. A summary of the final single patent document is created using sentences, SAO information, TEMPEST information, and problem/solution information defined using the output. The sentence is generated in text form by decoding the output embedding. SAO information is created in the form of a connected SAO structure by finding tokens with Subject, Action, and Object tags in the summary output token. TEMPEST information is generated in the form of the TEMPEST class that the summary token set has. If several TEMPEST classes are derived, information is provided by sorting them in the order of frequency. Problem/solution information is defined as the most expressed class among the problem/solution classes of the summary token set.

In the next step, Level 2, topic modeling is performed for the full patent text to categorize the summaries of a single patent. The topic model uses Latent Dirichlet Allocation (LDA) (Blei, Ng, & Jordan, 2003). LDA topic modeling, which is additionally learned in inference, assumes that documents are composed of a mixture of topics, and the topics generate words based on probability distributions. Fig. 6 illustrates LDA, where (α, β, K) indicates the hyperparameter value of Dirichlet distribution, M indicates the number of documents, N is the number of words in a document, θ is the Dirichlet distribution of topics in documents, φ is the words of the topic, Z is the number of the topic to which the word belongs, and W is the actual observable value. The learning process goes through an unsupervised learning process. In this learning process, when the number of topics K is given, documents and words (W) appearing in the documents are grouped for each topic. At this time, in a way that maximizes the ratio of between-class scatter and within-class scatter, documents and words are put into numbered topics one-by-one, and potential meanings (topics) are searched for. As a result of LDA modeling, document–topic matrix and topic–word matrix are derived.

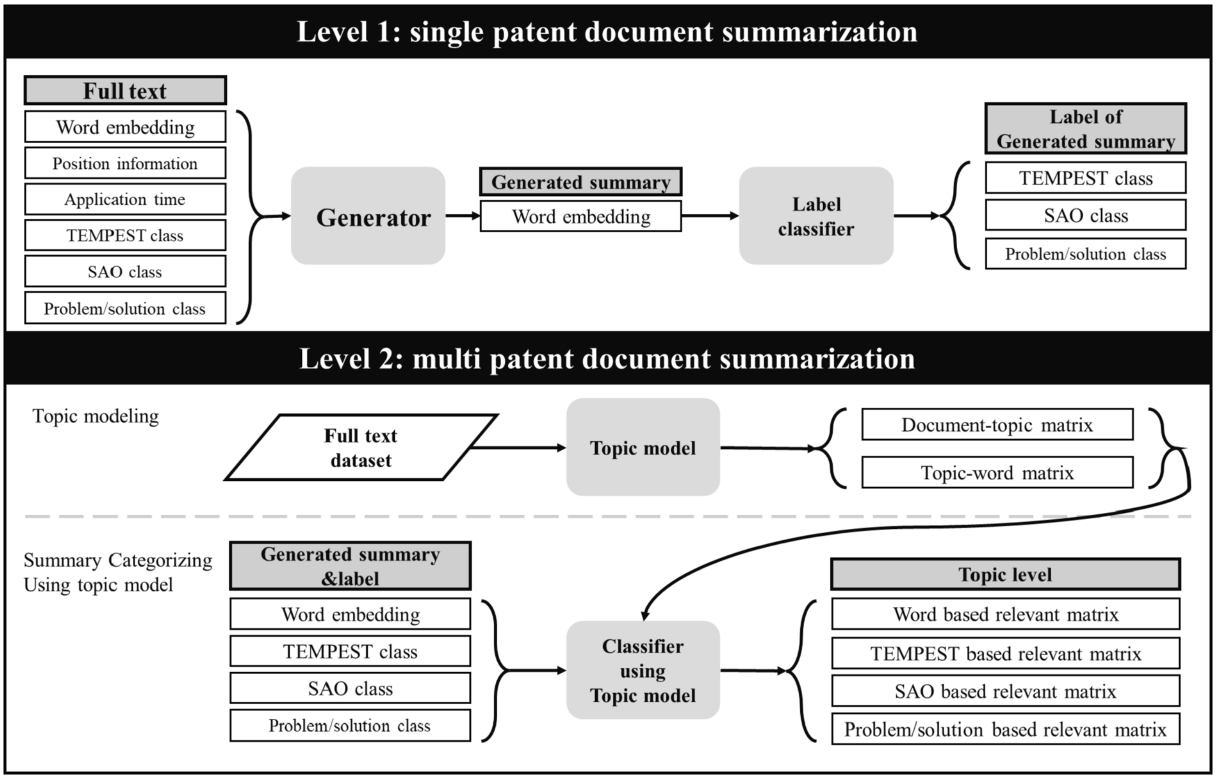

Fig. 5. Inference architecture.

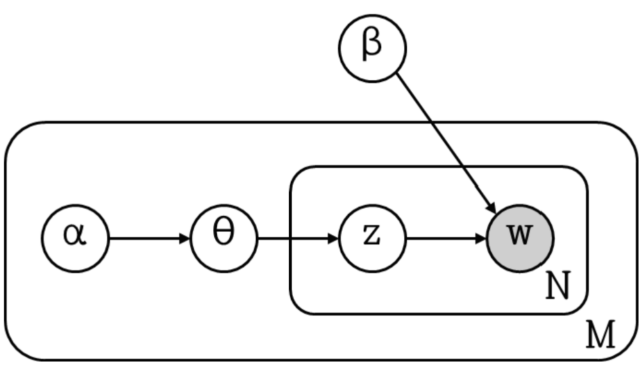

Fig. 6. Graphical model representation of LDA.

The document–topic matrix is a matrix with the size of number of documents × number of topics. This means the distribution (weight) of topics mixed in the document. By using a document–topic matrix, information, such as which topic a specific document belongs to, and which document is most closely related to a specific topic, can be derived. The topic–word matrix is a matrix with the size of the number of topics × number of words, meaning the distribution (weight) of words mixed within the topic. By using a topic–word matrix, information such as which topic a specific word belongs to, and which word is most related to a specific topic, can be derived. All patents are classified based on documents belonging to the derived topic model. To do this, first, the following four matrices are obtained from the topic level: Word-based relevant matrix, TEMPEST-based relevant matrix, SAO-based relevant matrix, and problem/solution-based relevant matrix. Since the distribution of documents for the topic is derived, a word-based relevant matrix about which topic a specific document is related to in terms of general words can be easily obtained. The TEMPEST-based relevant matrix and problem/solution-based matrix are calculated by weighting the word-based relevant matrix by the appearance of each class for each document. They are used to find documents that are highly relevant to each TEMPEST or problem/solution class in a particular topic. Finally, the SAO-based relevant matrix is calculated not at the document level, but at the SAO structure level. This is calculated through the topic–word matrix, topic–document matrix obtained through the topic model, and the topic information of the document including the SAO structure. First, the SAO structure–document frequency matrix, which is a matrix with the size of the number of SAO structures × number of documents, is calculated using the generated summary & label information. By multiplying the SAO structure–document matrix by the document–topic matrix obtained through topic modeling, the SAO structure–topic matrix from the document perspective can be obtained. In addition, by multiplying the SAO structure–word matrix expressing words constituting the SAO structure by the topic–word matrix-1, the SAO structure–topic matrix from the word perspective can be obtained. The final SAO-based relevant matrix is obtained by performing Hadamard product operation on the SAO structure–topic matrix from the document perspective, and the SAO structure–topic matrix from the word perspective. Finally, the document or SAO structure with the highest value in each relevant matrix is defined as a summary representing the topic from each point of view.

Fig. 7 shows the final patent summary that can be visualized. Patent documents are primarily classified based on topics derived from LDA topic modeling. A summary is presented for each classified topic. This summary is a Level 2 MDS. Summary sentences of individual patents for each topic, Level 1 SDS, are summary sentences generated by the generator. The abstract of each patent is presented together with the text, as well as the TEMPEST class, SAO class, and problem/solution class label.

4. Illustration: Drone technology

To evaluate the feasibility of the proposed model, we illustrate its use for patents in the drone technology field. Unmanned aerial vehicles (UAVs) or drones were initially developed for military purposes.

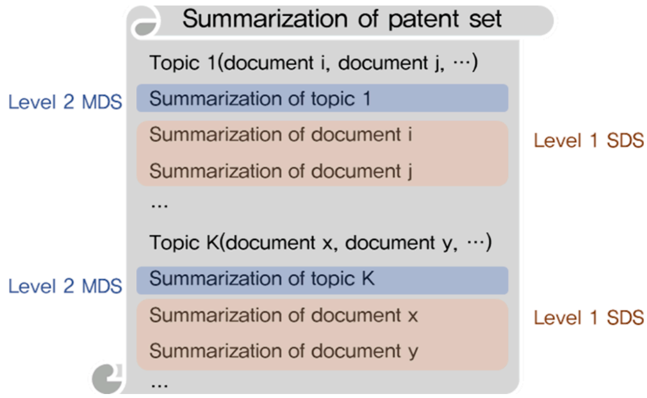

Fig. 7. Patent summarization inference.

However they have recently been used in various fields, such as traffic monitoring, *ad hoc* network construction in disaster areas, and delivery services (Chiang, Li, Shang, & Urban, 2019; Choi, Sung, Park, Ahn, & Kim, 2017). The application of drones can greatly reduce the cost and time required for conventional delivery systems. The drone is not limited to already established infrastructure, such as roads. In addition, by combining with an advanced communication system, it is possible to respond quickly to various events through instant updates. For this reason, many researchers consider drone technology as an innovative new technology that is expected to be used as routinely as today's smartphones (Clarke, 2014; Giones & Brem, 2017). The reasons why drone technology was selected as a technology to be analyzed in this study include the innovativeness and the diversity of technologies that make up drone technology. The drone technology field combines various other technological fields, such as communication, AI, and traditional manufacturing. Therefore, it can be said that it is an appropriate technical field by applying a model that generates a summary, considering the topic of the patent proposed in this study.

4.1. Dataset and data pre-processing

Patent documents were obtained by collecting published patent documents provided by the United States Patent and Trademark Office (USPTO). Table 3 shows the search queries used for the collection and general information of patents. A total of 3,195 drone-related patents registered between 2010 and 2020 were collected. By accessing the USPTO URL included in the table, all patents used in this analysis can be downloaded. The URL shows the result of searching for a query made through the patent search term using advanced searching of the USPTO Patent full text and image database. Among them, duplicate patents and outlier patents were removed, and 3,085 patents were selected as final analysis target patents. Collected patent data were converted into learning data through a patent feature extraction step. To train the summarization model, the full text and summary target text are needed. In this study, learning data were constructed using the patent title, abstract, claims, and detailed description. In the analysis, the pairs of training data (full text and target summary text) were defined as (claims and abstract sentences containing title phrase) and (detailed description and abstract). A total of 6,170 training data pairs were derived from 3,085 patents. Among them, 80 % of randomly selected data were defined as training data and the remaining 20 % of data were defined as test data. This divided dataset was used in the model learning process and the single patent summarization model evaluation process in Section 5.2 (comparison with state-of-the-art methods). However, splitting the data into training and test data was not applied to MPDS because there are no target data in summarizing multiple patent documents. Thus, for the comprehensiveness of the summary, in Level 2: MPDS step, it is performed using the entire data in Section 5.3 (reliability of generated multi-document patent summary). Full-text components have 346 tokens on average, while summaries have 62 tokens on average. To consider this result, truncating and padding were performed to make the length of the full-text sequence 400 words. The length of the summary text was set to become 64 words for the learning process.

Table 3
The collected data.

DB	US Patent (USPTO)
Patent Search term	drone, ufv, amv, aav, fda, uav, rpas, swarming, uas, usv, uad, automated, mobile, aerial, flying, digital, assistant, unmanned, remotely, piloted, aircraft, space, vehicle, unoccupied, system, device
Application date	20100101 ~ 20210101
Number of patents	3,195
USPTO URL	https://drive.google.com/file/d/1ibLXecVA-ozwqqk4Z9LnBAhc-KbzhIZg/view?usp=sharing

4.2. Experimental results

We trained the encoder and decoder of the generator, discriminator, and label classifier using Adam optimizer at a learning rate of 0.001. For the transformer of the generator and LSTM layer of the discriminator, we set the number of hidden units to be 512, and the embedding dimension of the embedding layer to be 128. We trained GAN models for 100 epochs. The discriminator was trained twice for one generator iteration. The label classifier model was trained for 50 epochs. The parameter of LDA is the number of topics k. The Topic Kullback–Leibler (KL) divergence index proposed by Arun, Suresh, Madhavan, and Murthy (2010) was used to find the optimal topic number. The index is computed in term of symmetric KL divergence of the topic–word matrix and L $\times$ document–topic matrix, where L is a 1 $\times$ document vector containing the length of each document in the corpus. The k with a low KL divergence value is determined as the most appropriate k. Consequently, the number of topics showing the best index value was selected as $k = 20$ in this paper. The LDA model was trained for 1,000 epochs.

As a result of learning, a summary of patent document units and a topic-level summary, which is a set of documents, are produced. The learning process proceeds in the order of SPDS and MPDS. We look at the results in the same order. Table 4 below is an example of the summary of a single patent. The generated summary text shows good similarity to the target summary. As sentences lengthen, the generated words differ slightly from the target summary. In addition, labels are generated by inputting the generated summary text into the label classifier. Further explanation is possible through these. SAO class, TEMPEST class, and problem/solution class are generated for each word token composing the generated summary. Words with S–A–O sequence among the generated SAO class sequences can be organized as SAO information. At this time, if the same SAO structure appears consecutively, such as S–S and O–O, two-word phrases are used as the structure. For each SAO structure organized by the defined SAO information, the TEMEPST information is organized using the TEMPEST class of the action word. Lastly, the class that occupies the greatest portion of the sentence among the problem/solution classes of words is organized as the problem/solution information. Patent US-10013611-B2 is a patent for a system and method for performing hydrological assay using drone technology. Comparing the full text, target summary, and generated summary, the generated summary sentences captured the purpose of the patent well. However, in the full text and target summary sentences, the content of "soil moisture sensor is needed for image processing" was turned into the content of "image includes target objects collected by UAV" in the generated summary sentences. As mentioned earlier, when creating a long sentence, the last part of the sentence tends to be poorly generated. Additional interpretation is possible using SAO, TEMPEST, and problem/Solution information extracted from the generated summary sentence. Component information of the patent can be obtained from the

Table 4
Example of Single Patent Document Summarization.

Patent No.	Type	Text	
US-10013611-B2	Full text	The present invention pertains generally to systems and methods for establishing long-term, conservation programs for selected topographical sites. More particularly, the present invention pertains to water conservation programs based on hydrological data that is remotely collected during an aerial hydrological-assay. The present invention is particularly, but not exclusively, useful for establishing water conservation programs to selected topographical sites which are based on a combined engineering assessment of image data, which is generated during an aerial surveying mission flown by an Unmanned Aerial System (UAS), and moisture data which is collected by ground-based moisture sensors. For environmental, commercial and political reasons, water conservation is an important consideration. Depending on numerous factors, such as just how much water is actually consumed for a particular purpose, water usage can vary substantially. In many instances, the cost of water usage can, and should, be controlled.At a commercial level, the cost for water usage is typically established merely by monitoring the volume of water that is used. The volume of water that is used, however, will necessarily depend on actual requirements, which will be site specific. In particular, for irrigation purposes, how water usage is managed is an important issue. For discussion purposes, and with a specific consideration for irrigation systems, consider golf courses.	
	Target summary	Systems and methods for performing an aerial hydrological-assay of a topographical site require the use of an Unmanned Aerial System (UAS) for collecting image data of the site. Included in a system for the present invention is a ground-based soil moisture sensor for collecting moisture data at the site. A computer is then used to combine the image data and the moisture data to create an assay report on hydrological conditions at the site. The assay report is used to implement a water conservation plan for the topographical site which efficiently and efficaciously controls water usage at the site.	
	Generated summary	Sentence	systems and method for perform a aerial hydrologicalassay of a topographical site require the use of the site pose include in a system surveillance for the site be obtain for the system for a unmanned aerial system lrb uav rrb image include a target object a surveillance for the uav be detect base on the site and collect
		SAO information	(1) system surveillance - include - site pose (2) UAV – detect – base
		TEMPEST information	(1) space (2) time
		Problem/solution information	solution

first SAO information, '(1) system survey-include-site pose'. The second '(2) UAV-detect-base' shows core functions performed by the UAV in the patent. Based on TEMPEST information: (1) space and (2) time, it can be inferred that this patent is an invention of a process and a patent describing a component. Finally, the problem/solution information 'solution' shows that the generated summary is the information summarized from the perspective of the technical solution of this patent.

As a result of learning the LDA model, parameters for the model can be obtained. The document–topic matrix and topic–term matrix can also be obtained. The document–topic matrix calculates the proportion of the topic belonging to the document for each document, while the topic–term matrix calculates the proportion of the term belonging to the topic for each topic. Using predefined topic information, terms with the highest relevance for each topic were extracted to see what each topic is, as shown in Table 5. When summarizing the information of patent documents using the existing LDA, it could be viewed only at the term level. However, the proposed framework provides various information on topics, in addition to word-level information. For documents belonging to the relevant topic, it provides a structural summary of the SPDS level discussed earlier. Among the summaries of each topic classes, we look at MPDS examples for topic 6 and topic 20 in detail.

In MPDS, a summary of the topic is presented first (Table 6). The word most relevant to topic 6 is 'battery'. In addition, through the top-15 more relevant terms, topic 6 is related to the drone's fuel, cell, battery charging, and charging stations. The most relevant documents and SAO structures to the topic are presented. In terms of TEMPEST and problem/solution information, summary sentences with the highest relevance to each class are presented. The most relevant summaries of each TEMPEST class and problem/solution class are presented, among summaries of documents belonging to the corresponding topic. Thus, the summary has the advantage of being able to look at the contents of various viewpoints of the topic at once. Among inventions that can be seen in the summary of topic 6, there is an invention of a battery using graphene that can replace copper wire from the material point of view of TEMPEST. From the perspective of TEMPEST's personality, research on how to wirelessly deliver the drone's battery and research on the charging system composed of multiple batteries from the perspective of the space of TEMPEST can also be confirmed. After presenting the summary of the

Table 5
The top-15 most relevant terms.

Topic	Top-15 Most Relevant Terms
Topic 1	fig, example, description, embodiment drawing, illustrate, uav, reference, diagram, aerial, vehicle, unmanned, figure, disclosure, image, number
Topic 2	datum, device, user, information, plurality, receive, method, network, request, base, associate, server, include, store, configure
Topic 3	antenna, comprise, end, connect, unit, casing, apparatus, body, voltage, surface, wall, material, beam, inner, reflector
Topic 4	uav, flight, location, area, vehicle, control, target, fly, determine, unmanned, information, path, base, receive, include
Topic 5	application, file, invention, incorporate, provisional, related, priority, entirety, continuation, claim, benefit, entitle, crossreference, field, relate
Topic 6	battery, charge, power, time, fuel, people, present, single, relate, effector, uass, range, challenge, failure, station
Topic 7	aerial, comprise, aerial, plurality, position, unit, vehicle, couple, surface, unmanned, vehicle, motor, direction, body, portion
Topic 8	energy, robot, launch, machine wind, pump, cell, fluid, launcher, water, volume, kinetic, tethered, means, power, underwater
Topic 9	application, patent, title, broadband, channel, method, us, file, background, incorporate, document, eg, reference, present, include
Topic 10	delivery, communication, network, service device, mobile, drone, wireless, package, deliver, user, transport, order, access, multiple, traffic
Topic 11	claim, comprise, uva, sequence acid, aav, fly, aerial, id, seq, method, encode, cell, recombinant, aerial, composition
Topic 12	item, carrier, node, cart, apply, patient, delivery, web, period, handle, center, order, fulfillment, sabot, reverse
Topic 13	unmanned, vehicle, aerial, use background, control, present, field, invention, application, relate, uav, aircraft, flight, autonomous, disclosure
Topic 14	filter, noise, audio, filmcage, valve, reduction, domain, result, seller, building, lens, ball, axial, web, rough
Topic 15	fly, comprise, configure, drone, tether, open, vibration, print, sound, attachment, apparatus, programmable, layer, body, container, water
Topic 16	power, electrical, product, container, configure, line, current, supply, source, electrically, electric, duct, energy, transport, circuit
Topic 17	particle, method, solution, head, gas, growth, iteration, step, produce, gate, step, contact, base, location, claim
Topic 18	datum, signal, vehicle, base, determine, receive, aerial, unmanned, location, processor, measurement, detect, condition, radio, plant
Topic 19	cell, vector, human, disease, expression, genome, virus, invention, b, aav, sequence, culture, therapy, dna, produce
Topic 20	drone, image, camera, capture video, object, include, use, property, fly, digital, base, view, datum, pixel, light

Table 6
Example of topic 6 multi patent document summary.

Topic 6		
Top-15 Most Relevant Terms		battery, charge, power, time, fuel, people, present, single, relate, effector, uass, range, challenge, failure, station
Top-3 Most Relevant documents		US-10363826-B2, US-10676191-B2, US-9284062-B2
Most Relevant SAO structures		(1) Battery system – take – control (2) battery capacity - limit - electric vehicle (3) base – comprise – power source (4) uav - include - recharge (5) container – include – recharge station
Most Relevant summary of each TEMPEST class	Time	–
	Energy	systems method and device be provide herein for improve the power performance of vehicle a hybrid power system may comprise a power controller adapt to detect whether a load along a first power source of the power performance of the drone a first load exceed a load a load the power fuel efficiency may divert
	Material	a graphene power generate system be connect to a rotate shaft or drive shaft of the vehicle or other move object those shaft be mainly waste energy that waste energy be re collectable by this nanographene alternator or generator when rotate the shaft new alternator or generator replace copper wire by super conductive and ultrastrong lightest material of the
	Personality	a system and method for convert onboard batterypower freeflight drone into groundpowered tethered drone that overcome the impediment design into safeguard freeflight drone in combination with a groundsourced power supply for the drone power be deliver to the drone through a tether the system comprise a battery emulate module that provide false signal to the drone battery circuit
	Space	rack system be provide that include a plurality of tray configure to hold a respective plurality of batterypowered uav and a frame configure to support the plurality of tray in a vertical arrangement each tray of the plurality of tray include a platform bumper and first plurality of electrical contact the platform may be configure to carry
Most Relevant summary of each problem/ solution class	Problem	method device and system of various embodiment be disclose for operate a uav have insufficient power to operate normally various embodiment include determine whether a emergency recovery state of a battery of the uav have be reach while the uav be fly a emergency recovery mode may be activate in response to determine that the emergency recovery state have be
	Solution	Uav configuration and battery augmentation for uav internal combustion engine and associate system and method be disclose a representative configuration include a fuselage first and second wing couple to and pivotable relative to the fuselage and a plurality of lift rotor carry by the fuselage a representative battery augmentation arrangement include a dcpowered motor a electronic
Summary of Patent US-10363826-B2	Generated Sentence	systems and method be provide for swap the battery on a unmanned aerial vehicle uav may be able to identify and land on a energy provision station autonomously the uav may take off land on the energy provision station the uav may communicate with the energy provision station the energy provision station may
	SAO information	(1) Uav – take - land
	TEMPEST information	(1) space
	Problem/ solution information	solution
Summary of Patent US-10676191-B2	Sentence	uav configuration and battery augmentation for uav internal combustion engine and associate system and method be disclose a representative configuration include a fuselage first and second wing couple to and pivotable relative to the fuselage and a plurality of lift rotor carry by the fuselage a representative battery augmentation arrangement include a dcpowered motor a electronic
	SAO information	(1) representative battery augmentation arrangement – include - dcpowered motor (2) configuration – include - fuselage (3) fuselage – carry – include
	TEMPEST information	(1) energe (2) material (3) space
	Problem/ solution information	solution
Summary of Patent US-9284062-B2	Sentence	a multizone battery station be provide comprise a plurality of landing area configure to support a uav the battery station may permit battery life to be reload onto a uav which may include recharge a battery of the uav or exchange the uav battery for a new battery the different zone may accommodate different uav type different
	SAO information	(1) multizone battery station – permit - battery life (2) uav - include - recharge (3) different zone – accommodate - different uav type
	TEMPEST information	(1) time (2) space (3) personality
	Problem/ solution information	solution

topic, the SPDS for the single patent reviewed earlier is presented. Documents that are highly related to the topic are provided in order. In this example, the top three documents are displayed. However, in actual use, the number of related documents set by the analyst can be reviewed. Summaries of patents US-10363826-B2, US-10676191-B2, and US-9284062-B, which are highly related to topic 6, show that they are related to drone batteries and charging.

In the case of topic 20, the MPDS is presented first (Table 7). Topic 20 is a drone technology related to image. Related keywords include drone, image, camera, object, digital, and pixel. As can be seen from the most relevant SAO structure, the main topics are 'operator to obtain image', 'process to extract image', 'camera or drone that takes image', and 'camera that transmits image'. TEMPEST's Time perspective summary presents the purpose and process of operation of the drone vision system. Its Space perspective summary presents inventions for multiple camera devices and control docks included in the drone video surveillance system. After summarizing the topic by point of view, a summary of the most relevant inventions is presented.

5. Validation and discussion

The viewpoints and contents of validation and discussion at the single document level and the multi-document level are different. Verification at the SPDS level was conducted by comparing it with other summary methodologies such as TextRank, LSTM, GRU, and Transformer summarization models. In the next section, evaluation metrics from the traditional NLP perspective and newly proposed evaluation metrics will be introduced. Then, a comparative baseline model is introduced and evaluation results with implications for each model are presented. The training and test data are applied to evaluate the performance of the models in SPDS. However, for MPDS level results, different approaches such as data reduction rate, readability, and fluency are used because the target data for MPDS cannot be obtained.

5.1. Evaluation metrics

Among existing language model evaluation indicators, Recall-Oriented Understudy for Gisting Evaluation (ROUGE) and Bilingual Evaluation Understudy (BLEU) scores are frequently used in the sentence generation and summary fields (Lin, 2004; Papineni, Roukos, Ward, & Zhu, 2002). ROUGE is calculated using Eq. (7) with a key assumption that a good key sentence should include many words or phrases that are identical to the correct target summary sentence. ROUGE is defined as ROUGE-1, ROUGE-2, ROUGE-n, and so on, according to the word window size of the phrase to be considered. ROUGE-n uses n-gram recall between reference summaries and target summaries as a performance evaluation measure. ROUGE-1 uses the recall value in unigram. ROUGE-2 uses the recall value in bigram. The BLEU score is also an index. It is used when input data and output data are words with order information, that is, sentences. It consists of concepts of precision, Brevity penalty, and clipping. Precision is a concept based on the assumption that a good key sentence, like ROUGE, should contain many words or phrases in the correct answer summary sentence. It measures how overlapping n-gram word phrases are. In the present study, 1 to 4 were used as the n of n-gram. Brevity penalty is an overfitting correction for sentence length. Overfitting for sentence length is the case where the generated sentence is too short compared to the correct sentence, or the case where the precision value increases because the number of overlapping n-grams increases as the generated sentence becomes longer. Minimum (1, length of predicted sentence/length of true sentence) is used as a penalty value. Clipping corrects overfitting when the same word appears consecutively. If there are duplicate words in the predicted sentence, the value is corrected in consideration of the maximum number of duplicate words in the correct sentence to correct this. The formula to obtain the final BLEU score is as given in Eq. (8) below:

$$ROUGE-n = \frac{numberofoberlappingn-grmas}{n-gramsinreference} = \frac{\sum_{S\in\{refer\}}\sum_{gram_n\in S}Count_{match}(gram_n)}{\sum_{S\in\{refer\}}\sum_{gram_n\in S}Count(gram_n)} \tag{7}$$

Table 7
Example of topic 20 multi patent document summary.

Topic 20		
Top-15 Most Relevant Terms for Topic 20		drone, image, camera, capturevideo, object, include, use, property, fly, digital, base, view, datum, pixel, light
Top-3 Most Relevant documents for Topic 20		US-10182225-B1, US-9442485-B1, US-10187580-B1
Most Relevant SAO structures		Operator – obtain – image image processing – extract – image element camera – capture – image vehicle – capture – image camera – transmit - image
Most Relevant summary of each TEMPEST class	Time	a vision system for a vehicle include at least one vehicle camera dispose at a vehicle so as to have a field of view exterior of the vehicle and a control that include a image processor operable to process image datum capture by the vehicle camera a aerial platform be dispose at the vehicle and be operable to detach from and
	Energy	a method and system may assess the damage to insure property in a neighborhood use aerial image capture from a unmanned aerial vehicle uav a manned aerial vehicle mav or from a satellite device specifically a neighborhood that have be affect by a natural or manmade disaster may be identify for assess damage
	Material	–
	Personality	image capture by a camera system of a unmanned aerial vehicle uav can be use to determine a weather condition in a environment of the uav the camera system of the uav can capture one or more image and a characteristic of at least one image of the uav the one or more image can capture by
	Space	a video surveillance system have a plurality of aerial camera device such as camera on drone operable from a plurality of docking station each station have a dock for receive charge and control the aerial camera device
Most Relevant summary of each problem/solution class	Problem	a method and system for measurement of ground base vehicle speed include a movable platform that include a unmanned aerial vehicle uav located in proximity to a roadway the uav operate under control and navigation of the uav operate under control and monitoring equipment the uav operate in some embodiment the uav include a onboard camera and
	Solution	a apparatus and method can be use with a remote vehicle such as a unmanned aviation system ua or unmanned aviation vehicle uav the system can be a apparatus include a camera electronics and a communication unit the electronics provide a display image on a combiner the camera be dispose to receive the
Summary of Patent US-10182225-B1	Sentence	image capture by a camera system of a unmanned aerial vehicle be use to determine a weather condition in

(continued on next page)

Table 7 (*continued*)

Topic 20		
		a environment of the uav the camera system of the uav can capture one or more image and a characteristic of at least one image of the uav the one or more image can capture by
	SAO information	(1) camera system – capture – image (2) uav – capture - by
	TEMPEST information	(1) personality (2) time
	Problem/ solution information	Solution
Summary of Patent US-9442485-B1	Sentence	pixel base image tracking system for unmanned aerial vehicle camera system
	SAO information	(1) System for unmanned aerial – tracking - pixel
	TEMPEST information	(1) personality
	Problem/ solution information	problem
Summary of Patent US-10187580-B1	Sentence	a action camera system for a unmanned aerial vehicle select a target base on a reference image capture by a onboard camera image processing determine a desired orientation of the target to the uav by which the uav can track the target and provide streaming video image from the desired orientation image processing establish a visual
	SAO information	(1) uav – orientation – target base (2) camera image processing – base (3) image – track - uav
	TEMPEST information	(1) time (2) time (3) space
	Problem/ solution information	solution

$$BLEUscore = \min\left(1, \frac{outputlenth(generated)}{referencelenth(target)}\right)\left(\prod_{i=1}^{4} precision_i\right)^{\frac{1}{4}} \tag{8}$$

In this study, we proposed evaluation indices that could additionally evaluate patent summaries other than ROUGE and BLEU. ROUGE and BLEU are values defined based on the appearance of words that constitute a sentence. Therefore, they cannot be used to evaluate technical content, or determine how well it makes sense grammatically, or whether it is human-readable. An $index_{key\_SAO}$ is an index that evaluates whether an important SAO structure or syntax is included. It is assumed that the more SAO structures that appear the same as the full text, the better the summary. Therefore, the $index_{key\_SAO}$ can be calculated with Eq. (9). The larger its value, the better the performance of the summary. $index_{key\_SAO}$ has the disadvantage that the important SAO structures or syntaxes need to be defined. However, it has the advantage that if the important SAO structures or syntax structures of patent information are well selected, it can intuitively express summary performance from a patent point of view. In this study, $index_{key\_SAO}$ was calculated using all SAO structures appearing in the full text, without defining the important SAO structures. An $index_{tf-idf}$ is an index calculated as the average value of the TF−IDF of words in summary sentences. Since the TF−IDF is an index indicating the importance of the corresponding word, a high TF−IDF of words in the summary can be interpreted as the summary being well generated with important words. Equation (10) shows this formula. An $index_{word-dist}$ is an index that shows the distribution of words of the summary (Eq. (11)). A large distribution of words can be interpreted as important words in the summary being evenly distributed. Although a high value of this indicator cannot be directly interpreted as a good summary, it can be indirectly interpreted as a good summary, because it means that the words constituting the summary are not biased. Therefore, in this study, the performance of summary sentences generated using these newly proposed indicators ($index_{key\_SAO}$, $index_{tf-idf}$, $index_{word-dist}$), in addition to BLEU and ROUGE, was evaluated.

$$index_{key\_SAO} = key\_SAOinsummary \tag{9}$$

$$index_{tf-idf} = average(TF - IDF(wordinsummary)) \tag{10}$$

$$index_{word-dist} = count(wordinsummary\&top - rankword) \tag{11}$$

5.2. Comparison with state-of-the-art methods

The baseline models used for comparison with the proposed model were: TextRank, LSTM, GRU, and Transformer-based summarization model. In addition to these baseline models selected for this study, various NLP models, such as Sequence to sequence with Attention (SSWA) and Big Bird, can also be used for document summary models (Trappey et al., 2020; Zaheer et al., 2020). However, most of these NLP models are improved models of the RNN-type model suitable for handling sequence information and attention-based transformer-type models. The SSWA model is an attention-based LSTM seq2seq model, while the Big Bird model is a Transformer-based model using sparse attention, one of the attention techniques. Therefore, in the present study, the TextRank model widely used in the early development of the text summary field, and LSTM, GRU, and Transformer-based summarization models, known to be the most popular models in the NLP field, were selected as comparison models. The selected models include all the base models of the advanced text generation models mentioned above. The TextRank summarization model used in this study was proposed by Mihalcea and Tarau (2004). The LSTM-based summarization model used in this study was a seq2seq model consisting of three LSTM layers in the encoder with one LSTM layer and one dense layer in the decoder. The GRU-based model had the same seq2seq structure as the LSTM-based model, having three GRU layers in the encoder with one GRU layer, and one dense layer in the decoder. For the transformer-based summarization model, the model proposed by Uszkoreit et al. (2017) having both the encoder and decoder configured with four stacks was used. TextRank, LSTM, and GRU-based models used features through general word embedding, rather than suggested features. The transformer conducted experiments in both cases using only the proposed features and general features. Training data and epoch were set to be the same as those when the proposed model was trained.

Table 8 shows the evaluation results using the traditional indicators ROUGE and BLEU. Overall, the performance of the transformer series, a model using attention, was significantly better than models such as TextRank, LSTM, or GRU that did not use attention. ROUGE-1, ROUGE-2, ROUGE-3, and BLEU all showed the same trend. The proposed model showed the second-best performance among all four indicators. The

Table 8
ROUGE and BLEU score by different methods.

Method	ROUGE-1 (F_1)	ROUGE-2 (F_1)	ROUGE-L (F_1)	BLEU
TextRank summarization model	0.2240	0.0720	0.1808	0.0075
LSTM summarization model	0.4006	0.1228	0.3838	0.0766
GRU summarization model	0.3982	0.1290	0.3841	0.0796
Transformer summarization model	0.8747	0.7642	0.8628	0.7557
Transformer summarization model & Proposed features	**0.9119**	**0.8238**	**0.9087**	**0.8250**
Proposed model & Proposed features	0.8842	0.7794	0.8763	0.7717

model using attention showed significantly improved performance over the models not using attention. However, its performance was less improved among models using the same attention mechanism. The model that showed the best performance as a result of evaluation using traditional indicators was the transformer summarization model with the proposed features. This means that the transformer summarization model using the proposed features is superior to the proposed model in terms of co-occurrence, the basic idea of calculating ROUGE and BLEU indicators. In other words, the two indicators indicate the degree of overlap of the same word or phrase with the target sentence. However, the overall BLEU score and ROUGE scores were lower than those of the SOTA models tested on non-patent data. This might be due to the long length of the text constituting the patent document, the complex structure, and the use of vague technical and legal words. This problem needs to be solved in future studies.

On the other hand, in the evaluation results using the proposed indicators, $index_{key\_SAO}$, $index_{tf-idf}$, $index_{word-dist}$, the proposed model showed the best performance (Table 9). The results for all models showed a similar trend to the evaluation using ROUGE and BLEU. Models using attention performed better than models not using attention. There was only a small difference between different models using attention. The proposed model also showed significantly improved performance over that of the models not using attention, although when compared to models using attention, its performance was only improved a little. In the evaluation using the $index_{key\_SAO}$, the proposed model showed better performance than the transformer summarization model with the proposed features, which is the model that showed the best performance in the evaluation using ROUGE and BLEU scores. This means that the proposed model generated a summary that better expresses the descriptive and structurally core content of the full patent text. A high $index_{tf-idf}$ score meant that the proposed model generated a summary that well included the keywords of the original document. Finally, a high $index_{word-dist}$ score indicated that the generation of summary sentences used more diverse words. In other words, the proposed model did not generate the same words or phrases in the target summary. With the proposed features, it was better than the transformer summarization model, as it generated a summary with better technical content and context. All these three metrics ($index_{key\_SAO}$, $index_{tf-idf}$, $index_{word-dist}$) can evaluate the generated summary in terms of the content of the patent. However, they cannot evaluate the fluency of the generated summary. Since the structure of the text constituting the patent is very complicated, it may be inappropriate to evaluate the fluency using the BLEU or ROUGE value. A proposal for a new fluency evaluation metric specific to a patent is needed.

In the above comparison with state-of-the-art methods, only SPDS validation was performed, whereas MPDS validation was not performed. This is because MPDS does not have validation data, making it impossible to evaluate the performance with other models using indicators. However, since the MPDS result proposed in this study was dependent on the result of the summarization of single patent documents, it could be said that the validation of the SPDS was also the validation of the MPDS as a result.

Table 9
Proposed evaluation metrics by different methods.

Method	$index_{key\_SAO}$	$index_{tf-idf}$	$index_{word-dist}$
TextRank summarization model	0.0000	2.2017	0.3364
LSTM summarization model	0.0001	2.5600	0.6407
GRU summarization model	0.0010	2.9900	0.6445
Transformer summarization model	0.1370	3.1726	0.8501
Transformer summarization model & Proposed features	0.1370	3.1912	0.8482
Proposed model & Proposed features	**0.1694**	**3.1969**	**0.8538**

5.3. Reliability of the generated multi-document patent summary

In this section, the generated summary is discussed to evaluate the MPDS in terms of data reduction, readability, and fluency. These were not discussed in the proposed evaluation metrics. One of the purposes of summarizing patent documents is to efficiently explore a large number of documents in a shorter time. From the point of view of efficiency, the generated summary can be evaluated with a reduction rate, which means how much the generated summary has been reduced, compared to the input document. The framework proposed in this study is divided into SPDS and MPDS. Since SPDS uses a supervised learning-based summary model, it is inappropriate to discuss the reduction rate. Since the MPDS result is presented as a summary of several patent documents structured in tabular form, the reduction rate can be discussed. For example, in Table 6, the final summary consists of 15 words most relevant to a specific topic (15 words), 3 most relevant documents (structured information), 5 most relevant SAO structures (on average, 20 words), a summary of the most relevant document for each class of TEMPEST and a summary of the most relevant document from the perspective of problem and solution (7 summary paragraphs in total; 448 words), SPDS summaries for the 3 most relevant documents (192 words), SAO structures (on average, 3 SAO structures, 12 words), TEMPEST information (structured information), and problem/solution information (structured information). In this study, the k calculated by applying the methodology proposed by Arun et al. (2010) was defined as the number of LDA topics. A total of k MPDS level summaries were generated. In this experiment, 20 MPDS level summaries were generated from 3,085 documents. A summary of one MPDS level consisted of approximately 687 words with additional structured information. Twenty summaries of an MPDS level consisted of approximately 13,740 words with additional structured information. Excluding structured information and considering only the number of words, the number of words in the MPDS summaries was reduced by approximately 99 %, compared to the 1,234,000 words constituting the full text of the 3,085 documents used for learning. However, this is a simple quantitative comparison. Since MPDS provides summaries of multiple perspectives and information on the words, SAO structures, and documents that are most relevant to the topic, it provides a wealth of information in addition to the amount. In addition, when using the framework, the analyst can define the length of the input full text, the length of the output summary text, and the number of highly related documents constituting the MPDS summary. Thus, the reduction rate can be adjusted according to the purpose.

The next point to be discussed is readability, meaning the degree of difficulty in obtaining information from the generated summary. In other words, readability can be defined as the degree of ease of reading. The MPDS summary presented in this study was created by topics. It consisted of representative information on the topic (Top-15 Most Relevant Terms, Top-3 Most Relevant documents, Most Relevant SAO structures), summary in terms of TEMPEST and problem/solution class in the topic, and detailed SPDS summary for representative documents of the topic. This information is structured and presented in tabular format, making it easy for analysts to find the information they want. Finally, MPDS can be discussed in terms of fluency. Fluency refers to the superiority of the quality of the text composing the generated summary. ROUGE and BLEU scores can be interpreted as indicators of fluency. However, the fluency we are discussing in this section is a higher level of fluency that includes accuracy of word or phrase, correct use of grammar, appropriateness of the vocabulary used, and naturalness and consistency of development. Examining the summary of the Energy in Table 6 in terms of the correct use of grammar, it can be found that the tense and form of verbs in phrases such as “systems method and device be provide herein” and “for improve the power performance” are incorrect. In addition to this, the generated sentences did not produce expressions suitable for tense, or number (singular or plural). Nor did they end with complete sentences. In terms of appropriateness of the vocabulary used, the general vocabulary was used appropriately. However, the specialized domain-specific vocabulary did not appear much. There are many sentences where the subject is “system”, “device”, “uav”, and so on. These subjects are frequently used in the Drone technology field. The verbs include “provide”, “comprise”, “include”, and so on. These verbs are frequently used in patents. Finally, in terms of the naturalness and consistency of the development, summary sentences were less natural and consistent toward the back of the summary. Although the summary was started with a structure appearing frequently in patents, such as “… system comprises…”, “… method for… structure such as”, many problems were found, such as repeating specific words and phrases, or generating words or words that were separated from the technical field. The summary presented in this study showed usable performance in terms of reduction ratio and readability. However, many points need to be improved in terms of fluency, which are also critical issues of generative language models to be solved. These limitations, also discussed in the previous section, suggest implications for challenges that need to be addressed in future studies.

6. Conclusion

This paper suggested a new method for summarizing multi-patent documents by using GAN algorithms with patent specific features and two-level inference architecture. Existing patent summary studies have mainly focused on rule-based methodologies from the point of view of a single patent summary. There are many manual processes, and they are domain specific. However, a comprehensive summary of the technology domain could not be presented. As a patent is a major document containing new scientific and technological knowledge, it is important to summarize a single patent. It is also very important to present an overall summary for numerous patents in a relevant field. Consequently, we proposed a method to summarize both single and multi-patent documents. The proposed analysis methodology includes a patent-specific feature extraction process, a summary model based on generative adversarial networks, and an inference process using topic modeling. This enables high-quality information summarization from a large number of patent documents. The methodology can be used to facilitate the activities of R&D researchers and decision makers. In addition, the features proposed in this study are specialized features for patent documents. Using these patent-specific features, better performance was obtained than from the models using existing general NLP features. Therefore, this study can be used as a guideline for future deep learning research using patent data.

The contribution of this study can be summarized as follows. First, we proposed an abstractive model to enable both SPDS and MPDS, unlike existing patent summary studies. Existing patent summary studies using text have focused on the single document. They are mainly rule-based or expert-based methods. Although deep learning has been attempted in previous studies, only extractive models have been presented. However, these models did not consider the characteristics of patents. In addition, the proposed model can generate summary text. It can also generate SAO, TEMPEST, and problem/solution classes indicating the characteristics of patents to enable richer analysis. Second, by applying patent text data to deep learning, patent-specific features were proposed, enabling learning that could better consider patent features. The experiment of this study showed that when patent-specific features were used, the learning performance was higher. In addition, the patent text showed the need for pre-processing and learning data composition methods different from existing methods, due to the characteristics compared to other text data. Finally, new indicators for evaluating patent summary methodology were proposed and tested. The existing patent summary evaluation methodology simply evaluated the summary based on the presence or absence of the same word phrase as the correct target sentence. The proposed indicators can be used to evaluate whether sentences with technological content, sentences with important words, and sentences containing various words are generated.

Although this study proposed a GAN-based patent summary model by successfully applying it to deep learning considering the characteristics of a patent, it did not consider all problems that might arise due to the characteristics of patent text. Patent text, especially patent claims, has a deep depth tree structure, because modifiers are longer and more numerous than in other texts. This is a very unfavorable condition, even when using a pre-learning model learned with an existing general natural language. Therefore, better performance can be obtained by separating them and pre-processing them to reduce the length of the sentence. In this regard, there is a research field for patent claim split. However, as it is mainly rule-based to study the readability of patent claims, it is necessary to study patent claims as a pre-processing process for application to deep learning. Another reason why deep learning using patent text is difficult lies in the characteristics of words that make up patent text. Since a patent is a technical document that describes a novel invention, domain-specific words, such as technical terms and abbreviations, are often used. This characteristic increases the sparsity of words, making it difficult to learn patents, compared to general plain texts. To overcome this, additional pre-processing, such as synonym processing and technology domain-specific term processing, can be performed. The document to be summarized in this study provides patent data describing inventions that are the result of creative problem-solving. To reflect this concept, the SAO structure of TRIZ was used to construct the learning input feature. However, the SAO structure is a very small part of TRIZ. The framework proposed in this study does not reflect the core concepts of TRIZ, such as contradiction or IDM. Because a better summary is possible if there is information on important parts of a specific document, a better patent summary can be achieved by using additional information, such as contradiction and IDM. Therefore, as one of the directions for future research, developing a summary model that reflects the core part of a patent using an attention method can be considered. By applying the GAN, this study trained the discriminator to discriminate whether the generated sentence and the target sentence were generated or not. It is expected that more effective text learning using GAN will be possible if it is used to learn additional information, such as “how well a sentence is generated”, not just whether a sentence is a generated sentence or not. Finally, there is a need to apply and test various NLP deep learning models to the generator of the GAN model. The methodology proposed in this study is a GAN-based summarization model, a structure in which a generator and a discriminator compete and learn, and a two-level summary framework using the summarization model. Therefore, various modifications other than the experimental settings and models used in this paper are possible. Also, in the experiment, the proposed model was only compared with four models: TextRank, LSTM, GRU, and the Transformer-based summarization model. Experiments with more models are expected to provide richer implications.

CRediT authorship contribution statement

Sunhye Kim: Conceptualization, Data curation, Visualization, Writing – original draft, Methodology, Software, Validation. **Byungun Yoon:** Conceptualization, Supervision, Investigation, Methodology, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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