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A Study on a Webtoon Recommendation System with Autoencoder and Domain-specific Finetuing Bert with Synthetic Data Considering Art Style and Synopsis

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***Abstract*—As the global webtoon market experiences rapid and substantial growth, webtoon platforms increasingly recognize the critical need for customized recommendation services that effectively utilize advanced user personalization technology. This strategic approach is essential for strengthening their market competitiveness in an increasingly crowded digital landscape. Conventional recommendation systems typically rely on content-based or collaborative filtering techniques, primarily measuring user similarities. However, these traditional methods often lead to significant challenges, such as the cold start problem and difficulties with long-tail deployment, primarily due to insufficient user data, especially for new or niche content. We propose an innovative recommendation algorithm based on a sophisticated autoencoder architecture to address and overcome these persistent challenges. Our approach involves a comprehensive evaluation of this algorithm alongside specialized art style and synopsis analysis algorithms. This multi-faceted algorithm is designed to extract hidden features from various components of webtoons and utilizes advanced clustering techniques through in-depth similarity analysis. This process enables the system to precisely determine intricate connections between individual webtoons. Furthermore, we implement a specialized autoencoder for style feature extraction in the art style analysis component to enhance and refine our approach. Complementing this, we employ a domain-specific BERT-based model, augmented with extensive data augmentation techniques, for comprehensive synopsis similarity analysis. In this study, the strategic use of autoencoders allows for the efficient and accurate reconstruction of important features from both the art style and synopsis of webtoons. This innovative approach results in a significantly more robust, scalable, and effective recommendation system, capable of handling the diverse and evolving nature of webtoon content.**

***Keywords*— Webtoon; recommendation system; feature extraction.**

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I. INTRODUCTION

Recently, as smartphones have become popular and communication technology has developed, they have become a popular cultural product with the advantages of short consumption time and quick accessibility. Additionally, starting with COVID-19, the webtoon market has proliferated as non-face-to-face popular culture products are preferred [1]. According to a market research agency report, the size of the global webtoon market is expected to grow from $4.7 billion in 2021 to $60.1 billion in 2030 at an average annual growth rate of 40.8% [2].

Amid fierce competition in the webtoon market, each platform provides users with various options. Users focus more on webtoons that suit their tastes and preferences as options expand. This preference is subdivided into multiple aspects, such as the story, art style, and main character's charm. Therefore, each webtoon platform approached the market using personalization technology as its primary technology [3]. User personalization technology allows users to access their preferred content more conveniently within the platform [4]. Therefore, if the various tastes of each user are analyzed and customized recommendation services are provided based on personalization technology, the size of the webtoon market will grow further.

The conventional personalized recommendation system introduced collaborative filtering and content-based filtering. This filtering technique measures similarity based on user-based interests, preferences, and observed behavior [5]. However, such a recommendation system has a cold start problem that makes it difficult to introduce in long-tail distribution, where promotions are applied only to options frequently accessed by users and when data accumulation is insufficient [4]. Additionally, recommendation systems are only based on the user's interest in options and do not reflect the unique characteristics of each content [6]. Therefore, to overcome these limitations, we propose a recommendation system for each webtoon, an autoencoder-based style similarity inference, and a domain-specific BERT-based recommendation algorithm [7].

II. Materials and Method

A. Data Acquisition

Synopsis and art style are the first features users encounter among the various components of webtoons. When designing a recommendation system, we extract the features of each webtoon and measure the similarity of features between webtoons. For this system, clustering and feature engineering were applied to extract and analyze features for each webtoon. For this experiment, we use the webtoons of the Naver Webtoon Platform [8]. The raw data set consists of the 588 labeled webtoon image data (Fig. 1) and 1,632 webtoon synopsis data (Fig. 2).

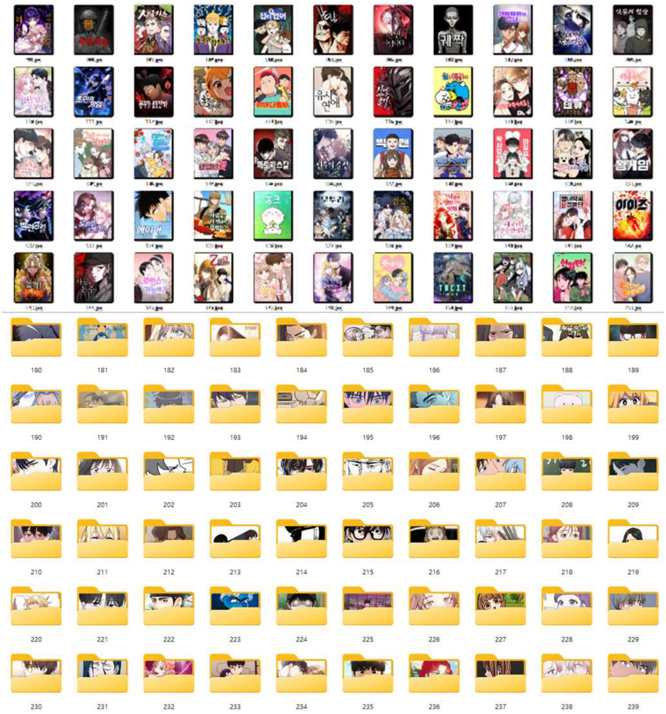

Fig. 1 Example of a webtoon image dataset

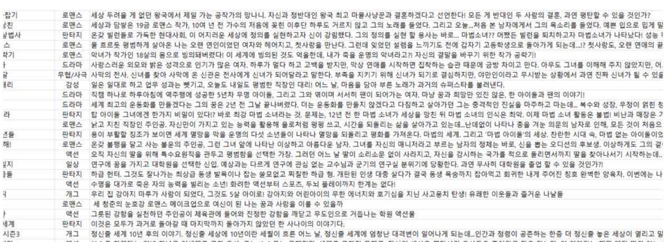

Fig. 2 Example of webtoon synopsis dataset

B. Recommendation System CNN-based and Pretrained General Bert

The art style-based Similarity Analysis is two methods feature extraction using CNN and clustering using PCA[9]. The feature extraction step selects a specific section for the calculation style loss. Then, the feature values of the art style are extracted by dividing the style into its components[10]. This method extracts the features of the webtoon's art style. Style transfer uses existing CNN generators to extract features from images. The style features select the features of the art style using the Gram Matrix. The loss function used in learning to choose the most valid style features is Eq. (1).

$$L_{style}(\vec{a},\vec{x}) = \sum_{l=0}^{L} w_l E_l \tag{1}$$

The clustering step inputs the webtoon art style's feature vector values [11]. The feature values of the webtoon art style are the characteristics of the CNN model and are output as high-dimensional vector values. After fast and efficient dimensionality reduction through PCA, clusters are formed based on k-means clustering and the Elbow method, as shown in Fig. 3 [12] [13].

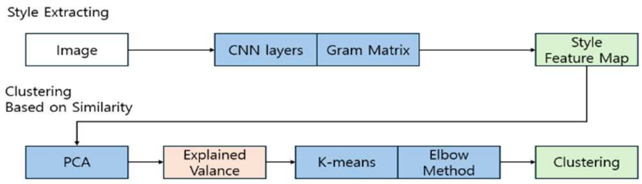

Fig. 3 A clustering based on similarity using style transfer architectures

The synopsis-based similarity analysis uses sentence similarity measurement and feature extraction using natural language processing. Feature extraction consists of the BERT model, which is the Transformer model's multi-layered model. This model extracts the embedding vector and trains rare words, core words, and context based on their frequency of occurrence, as shown in Fig. 4.

a. Token Embedding: Combining often arising long subcategory words into a single unit.
b. Segment Embedding: This is the process of composing words separated into tokens into sentences and then discriminating them.
c. Position Embedding: This is the process of encoding the sequence of each token.

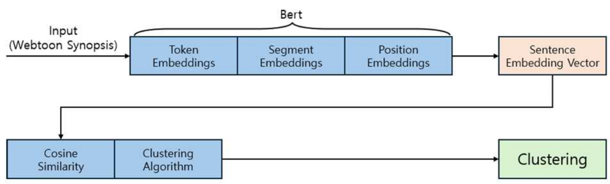

Fig. 4 A clustering based on similarity using BERT(STS model) architectures: Input webtoon synopsis data to obtain an embedding vector of the sentences within the synopsis. Measure the cosine similarity of derived values to group webtoons with similar synopsis.

Due to its characteristics, the BERT model shows excellent performance in entity recognition and intent classification and can be applied to a variety of sentences. Therefore, the BERT model is most suitable for webtoon synopsis analysis because the analysis of webtoons requires feature extraction considering genre context and core keyword extraction [14].

Using BERT-based word embedding, sentences in the synopsis are output as vectors, cosine similarity is derived, and sentences are classified into clusters with high similarity. The expression is shown in Eq. (2).

$$Similarity = \frac{A \cdot B}{\|A\|\|B\|} = \frac{\sum_{i=1}^{n} A_i \times B_i}{\sqrt{\sum_{i=1}^{n}(A_i)^2} \times \sqrt{\sum_{i=1}^{n}(B_i)^2}} \quad (2)$$

C. Proposed AutoEncoder-based and Domain-specific Finetuning Recommendation System

An autoencoder-based art style-based Similarity Analysis has two stages: training the autoencoder to extract hidden features and obtaining representative vectors of art style features for each webtoon through similarity analysis. As a feature extractor, the trained encoder extracts feature vectors of art styles.

d. Encoder: Compresses input data into a lower-dimensional latent space, extracting essential features.
e. Decoder: Reconstructs input data from latent variables, evaluating latent space representation.

The autoencoder model(Figure 5) is trained with a 4-layer encoder and a 4-layer decoder with a symmetric structure. It excels at learning various artists' styles without fixed patterns.

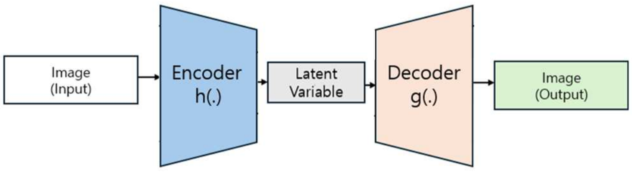

Fig. 5 The architecture of Autoencoder before training

The feature extractor obtains and uses only the feature vectors. When the input image is dimensionally reduced to latent variables through the encoder, the similarity is measured based on these vector values [15]. The loss function used for training the encoder is to maximize the Evidence Lower in the case of a variational autoencoder. This consists of reconstruction. The expression is shown in Eq. (3).

$$L = -E_{q(z|x)}[\log p(x|z)] + KL(q(z|x)\|p(z)) \quad (3)$$

The domain-specific finetuning of BERT has two stages: data generation and finetuning [16][17]. In this study, GPT-4 is used as the Closed LLM to generate a train STS dataset specialized in the webtoon domain, focusing on genres such as fantasy, martial arts, and thriller, by querying with a defined template, as shown in Fig. 6 [18][19].

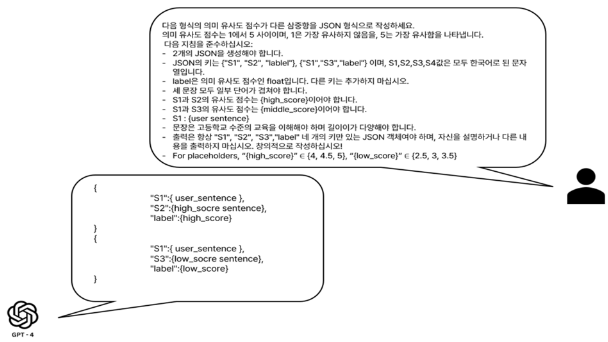

Fig. 6 Prompt template example for Korean webtoon STS, For placeholders, "{high_score}" ∈ {4, 4.5, 5}, "{low_score}" ∈ {2.5, 3, 3.5}

A test STS dataset is constructed using Korean sentence data augmentation techniques based on the generated paired dataset [20], [21].

TABLE I
METHODS FOR NLP DATA AUGMENTATION

Methods	Original	Augmentation
Random Deletion	**여자도** 군대에 간다면? 본격 여자도 **군대**가는 만화	군대에 간다면? 본격 여자도 가는 만화
Synonym Replacement	자신의 **모든** **것**이었던 **소녀**를 쫓아 탑에 들어온 소년 그리고 그런 **소년**을 시험하는 탑	자신의 **전부**이었던 **여자 아이**를 쫓아 탑에 들어온 소년 그리고 그런 **남자 아이**을 시험하는 탑
Random Swap	'**당신**이 부른 것이오. **나**란 사람을... ' **은둔고수 광휘**. **호위무사** 되다.	'**나** 부른 것이오. **당신이란** 사람을... ' **호위무사 은둔고수**. **광휘** 되다.
Random Insertion	평범한 뱃사공으로 살고 있는 노소하. 하지만 그의 정체는 전설적인 구파검법의 후계자다. 이제 진시황이 남긴 비서 선근경을 향한 살수행이 시작된다.	평범한 뱃사공으로 살고 있는 **소년가장** 노소하. 하지만 그의 정체는 전설적인 구파검법의 후계자다. 이제 **전설의** 진시황이 남긴 비서 선근경을 향한 살수행이 시작된다.

The custom dataset and the augmented dataset are then unified. Based on this unified dataset, the data is split, and a pre-trained BERT model is fine-tuned to perform similarity analysis of synopses in a recommendation system using embedding vectors [22].

D. Evaluation Methods

The evaluation aims to measure the performance of the recommendation system, which takes user webtoon usage data as input and outputs a recommendation list. In this evaluation, the recommendation system's accuracy and recall are measured and recorded using a confusion matrix based on the recommendations' input and output [23].

- TP (True Positive): Webtoons recommended by the system that the user actually chose.
- TN (True Negative): Webtoons recommended by the system that the user did not choose.
- FP (False Positive): The system does not recommend webtoons; the user chooses them.
- FN (False Negative): Webtoons not recommended by the system or chosen by the user.

TABLE II
CONFUSION MATRIX FOR WEBTOON RECOMMENDATION MODEL

	Predicted Positive	Predicted Negative
Actual Positive	True Positive (TP)	False Negative(FN)
Actual Negative	False Positive (FP)	True Negative(TN)

For the confusion matrix's output, the recommendation system's input data is the preferred webtoon list collected from users through surveys. Precision and Mean Average

Precision (MAP) are measured by comparing the recommended webtoons chosen by the user (TP) with the entire list of possible recommendations (Truth Grounds), such as Table II and Fig. 8 [24].

Fig. 7 Sample of Input data collection survey questions

The proportion of webtoons the user selects from the recommended list is considered a good result if it is close to 1. The equation is in (4).

$$Precison = \frac{TP}{TP+FP} \quad (4)$$

MAP is measured for all users to obtain an average precision across the user base. The equation is in Eq. (5).

$$MAP@K = \frac{1}{|U|}\sum_{u=1}^{U}(AP@K)_u \quad (5)$$

Using survey data from 120 respondents in Fig. 7, the recommendation system is evaluated on 588 webtoons serialized on platform Naver. The evaluation includes:

- Randomly extracting 25 samples from all respondents to measure MAP.
- Randomly extracting 50 samples from all respondents to measure MAP.
- Randomly extracting 75 samples from all respondents to measure MAP.
- Randomly extracting 100 samples from all respondents to measure MAP.

The data required for measuring evaluation metrics include the recommendation system's output based on user preferences and all possible webtoon recommendations. The webtoons used are from platform Naver's free serialized webtoon list, which has the highest user engagement. The survey target group consists of users in their 20s and 30s, irrespective of gender [25].

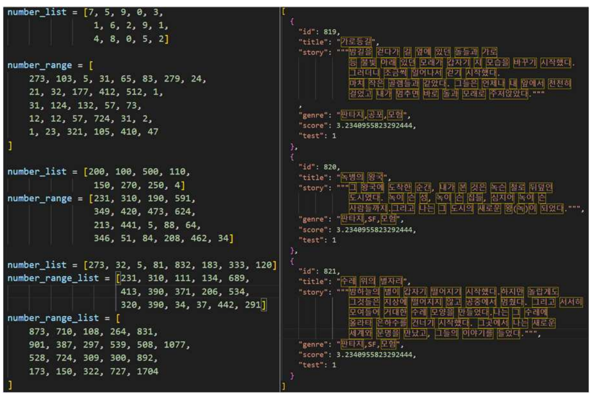

Fig. 8 Defining the Printable List for Ground Truth Settings

A random survey is conducted targeting this age group to collect 100 samples, such as Fig. 9. Data collection is undertaken via surveys, where users select their preferred webtoons by genre to form the model's input data. Non-selected webtoons from the recommended list are defined as FP data.

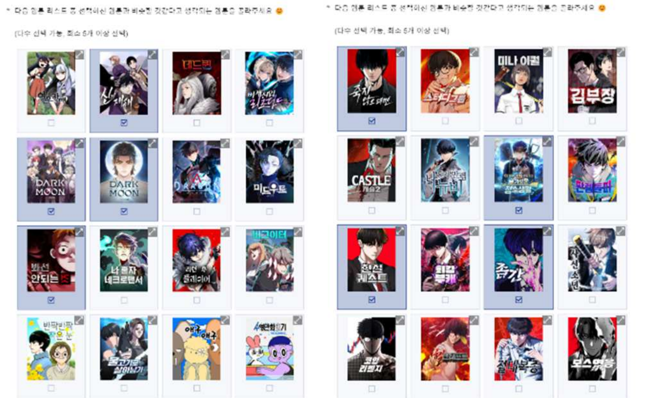

Fig. 9 Questions for User Webtoon Selection to Define TP and FP Data

The recommendation system's performance is evaluated by measuring the Average Precision per user and calculating the Mean Average Precision across all users. This indicates how well user preferences are reflected and how high the relevant items rank in the recommendation list.

III. Results and Discussion

In this study, we experiment with two webtoon recommendation systems that analyze two webtoon components, synopsis and art style, and compare their performance [26]. The first system combines a CNN-based image similarity analysis model with a recommendation system utilizing a pre-trained model with good results. Using synthetic data, the second system combines an AutoEncoder-based image similarity analysis model with a domain-specific fine-tuned BERT model. We measure user satisfaction with each webtoon recommendation system [27]. Therefore, in this study, we conducted user response-based experiments to select the most efficient feature extraction algorithm that produces the best similarity measurement and clustering results based on the performance indicators of individual algorithms. The user response data for measuring the mAP(mean Average Precision) of the first system, which combines a CNN-based image similarity analysis model with a recommendation system utilizing a pre-trained model that has shown good results, has been collected from a total of 120 participants as of November 17, 2023.

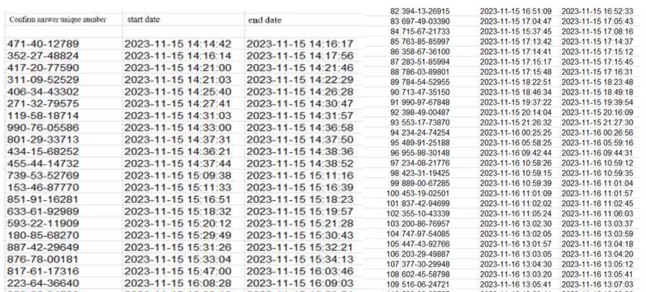

Fig. 10 Response for the recommendation system combining a CNN-based image similarity analysis model with a pre-trained BERT model

Similarly, the user response data for measuring the mAP of the second system, which combines an AutoEncoder-based image similarity analysis model with a domain-specific fine-tuned BERT model using synthetic data, had been collected from 120 participants as of June 11, 2024.

Confirm answer unique number	start date	end date	105-18-89898	2024-06-09 15:15	2024-06-09 15:20
102-19-71177	2024-06-05 0:00	2024-06-05 0:03	985-26-92602	2024-06-09 17:52	2024-06-09 17:53
672-83-64567	2024-06-05 0:05	2024-06-05 0:19	937-18-63414	2024-06-09 18:35	2024-06-09 18:36
734-98-67382	2024-06-05 7:16	2024-06-05 7:23	804-17-98482	2024-06-09 19:06	2024-06-09 19:11
714-14-67455	2024-06-05 9:59	2024-06-05 10:03	566-13-56579	2024-06-09 20:14	2024-06-09 20:21
102-12-14700	2024-06-05 11:02	2024-06-05 11:13	641-81-27526	2024-06-09 20:22	2024-06-09 20:26
517-14-37055	2024-06-05 11:26	2024-06-05 11:38	950-87-87949	2024-06-09 20:47	2024-06-09 20:59
136-36-60558	2024-06-05 14:33	2024-06-05 14:44	853-60-36180	2024-06-09 23:05	2024-06-09 23:07
376-53-59187	2024-06-05 15:10	2024-06-05 15:11	478-38-37359	2024-06-09 23:34	2024-06-09 23:39
463-64-62169	2024-06-05 15:29	2024-06-05 15:32	539-71-55939	2024-06-09 23:41	2024-06-09 23:52
805-68-16899	2024-06-05 18:49	2024-06-05 18:53	311-17-41614	2024-06-09 23:49	2024-06-09 23:50
574-26-73329	2024-06-05 19:07	2024-06-05 19:09	475-79-91629	2024-06-10 0:00	2024-06-10 0:03
396-74-55636	2024-06-05 19:30	2024-06-05 19:39	121-87-93433	2024-06-10 0:30	2024-06-10 0:32
550-64-65645	2024-06-05 21:20	2024-06-05 21:31	876-12-54852	2024-06-10 10:14	2024-06-10 10:23
691-75-23246	2024-06-05 21:42	2024-06-05 21:51	728-18-38543	2024-06-10 10:34	2024-06-10 10:46
583-12-57944	2024-06-06 11:17	2024-06-06 11:20	325-11-86371	2024-06-10 15:00	2024-06-10 15:12
304-27-54045	2024-06-06 12:36	2024-06-06 12:47	709-78-42005	2024-06-10 15:28	2024-06-10 15:41
517-15-40394	2024-06-06 14:01	2024-06-06 14:11	310-17-97333	2024-06-10 20:16	2024-06-10 20:24
489-12-88754	2024-06-06 14:23	2024-06-06 14:27	623-11-17960	2024-06-10 21:34	2024-06-10 21:42
358-11-81993	2024-06-06 14:41	2024-06-06 14:46	305-16-30437	2024-06-11 1:38	2024-06-11 1:50
822-15-20726	2024-06-06 15:31	2024-06-06 15:43	869-71-70145	2024-06-11 7:10	2024-06-11 7:19
412-82-71017	2024-06-06 15:50	2024-06-06 15:54	238-12-93627	2024-06-11 7:23	2024-06-11 7:34
474-18-81108	2024-06-06 18:22	2024-06-06 18:33	765-18-55316	2024-06-11 8:59	2024-06-11 9:11
724-16-53673	2024-06-06 18:25	2024-06-06 18:39	856-39-71124	2024-06-11 11:25	2024-06-11 11:32
361-13-69565	2024-06-06 18:30	2024-06-06 18:35	304-19-86510	2024-06-11 14:46	2024-06-11 14:51
719-35-10515	2024-06-06 21:10	2024-06-06 21:14	489-61-71239	2024-06-11 15:05	2024-06-11 15:11
639-91-62612	2024-06-06 21:15	2024-06-06 21:21	935-13-79149	2024-06-11 15:17	2024-06-11 15:25
558-90-83879	2024-06-07 1:13	2024-06-07 1:28	109-16-69240	2024-06-11 17:49	2024-06-11 17:50

Fig. 11 Response for the recommendation system combining an Autoencoder-based image similarity analysis model with a domain-specific finetuned BERT model

A. Experimental Results of Recommendation System CNN-based and Pretrained General Bert-based

We used the silhouette coefficient as the metric of evaluation[28]. The silhouette coefficient refers to the distance between each cluster group derived using the algorithm and the index distance that measures the distance between elements within the cluster (it ranges from -1 to 1). Successful clustering occurs when the silhouette coefficient is close to 1. The formula for the silhouette coefficient is Eq. (6).

$$s(i) = \frac{b(i)-a(i)}{max\{a(i),b(i)\}} \tag{6}$$

VGG19 is a conventional CNN model that extracts art styles in Style Transfer [10]. However, compared to their performance, the VGG series models do not exceed the human recognition error rate and are easy to overload. Therefore, we considered two models of VGG19 and ResNet50, and experiments were performed using these two models (Table 3).

TABLE III
PERFORMANCE OF DIFFERENT COLOR MODES, CNN MODELS, AND ARCHITECTURES

	Evaluation Metrics		
Model	**Color Mode**	**Num of Cluster(K)**	**Silhouette Coefficient**
VGG19	RGB	34	0.48
	Gray	18	0.53
Resent50	RGB	47	0.68
	Gray	26	0.52

As shown in Table III, the Resnet50 model on the 588 webtoons data derived the highest extraction value, 0.68, in the RGB Image color mode. Also, the most optimized cluster(K) value is 47. The evaluation indices are the Spearman and Pearson correlation [29]. The Spearman correlation coefficient is utilized to assess monotonicity, which measures the statistical dependence of the specific two variables. The equation is Eq. (7).

$$SROCC = 1 - \frac{6}{M(M^2-1)} \sum_{i=1}^{M} d_i^2 \tag{7}$$

The Pearson correlation coefficient is an indicator that measures the level of the linear association between the specific two variables. This means that a ratio value is obtained by dividing the covariance by the product of the standard deviation (It ranges from -1 to 1). The equation is Eq. (8).

$$PLCC = \frac{\sum_{i=1}^{M}(X_i-\bar{X})(Y_i-\bar{Y})}{\sqrt{\sum_{i=1}^{M}(X_i-\bar{X})^2(Y_i-\bar{Y})^2}} \tag{8}$$

Learning was performed using the KLUE-RoBERTa model [30], an open-source published on Huggingface, among the Korean BERT models.

TABLE IV
PERFORMANCE BERT MODEL (STS MODEL)

Model	**Cosine Pearson**	**Euclidean Spearman**	**Manhattan Pearson**	**Dot Spearman**
KLUE-RoBERTa	0.875	0.854	0.855	0.849

The webtoon recommendation system employs the algorithm outlined in Table 4. We evaluated the system's performance using previously established methods. Survey responses provided the data for calculating the Mean Average Precision (mAP). The system achieved an average mAP of 50.5%.

B. Experimental Results of Proposed AutoEncoder-Based Recommendation System

The autoencoder model's performance was evaluated using the mean squared error (MSE) as an evaluation metric [31]. The MSE measures the average squared difference between the actual and predicted values and is used to assess the quality of the reconstructed inputs from the latent space. The formula for the MSE is shown in Eq. (9).

$$MSE = \frac{1}{n} \sum_{i=1}^{M} d_i^2 \tag{8}$$

TABLE V
RECONSTRUCTION ERROR OF TRAINED AUTOENCODER MODEL

Metric	**Value**
MSE(Image)	0.032

The low MSE values for images indicate that the autoencoder model effectively captures the essential features of the input data and reconstructs them with high accuracy.

The webtoon synopsis data collected from each model was then converted to semantic textual similarity(STS) data for fine-tuning with a custom-created STS dataset(Figure 12) better to suit the specific characteristics of the recommendation system used in the experiments(TABLE 6) [32] . The experiment results are depicted in TABLE 6.


```
    "sentence2": "사람들이 건물 주변에 모여있다.",
    "labels": {"label": 1.0}
},
{
    "sentence1": "난 너 같은 짐승들을 상대하려고 변호사가 됐지.",
    "sentence2": "나는 너와 같은 사람들을 대응하기 위해 법률가가 되었다.",
    "labels": {"label": 5.0}
},
{
    "sentence1": "난 너 같은 짐승들을 상대하려고 변호사가 됐지.",
    "sentence2": "그는 불공평함에 맞서 싸우기 위해 법률 전문가로서의 길을 선택했다.",
    "labels": {"label": 4.4}
```


Fig. 12 Example of custom-created STS datasets for fine-tuning

TABLE VI
PERFORMANCE OF DIFFERENT BERT MODELS(CUSTOM TEST DATASET EVALUATION) BEFORE AND AFTER FINE-TUNING WITH OUR CUSTOM WEBTOON STS TRAIN DATASETS. BATCH SIZE AND EPOCH WERE SELECTED TO GIVE THE MOST OPTIMAL VALUES [33].

Model	Cosine Pearson	Euclidean Spearman	Manhattan Pearson	Dot Spearman
KLUE-RoBERTa	0.757	0.745	0.735	0.794
After FT	0.772	0.789	0.805	0.8

When fine-tuning the KLUE-RoBERTa base model with our custom STS dataset, we observed an improvement in sentence similarity analysis by approximately 2% to 4% in the webtoon story domain [34], [35]. The webtoon recommendation system, which utilizes the algorithm, achieved an average mAP result of 65.1% from survey responses, as defined by the previously established evaluation methods.

IV. CONCLUSION

This study experimented with art style and synopsis analysis techniques to enhance the performance of webtoon recommendation systems, proposing an autoencoder-based analysis technique coupled with a domain-specific fine-tuning method. The key findings of our research can be summarized as follows: The combination of an autoencoder model and a domain-specific fine-tuned BERT model outperformed the conventional combination of CNN-based models and general BERT models, improving the average mAP from 50.5% to 65.1%. The autoencoder model effectively extracted and reconstructed crucial features from webtoon art styles, as evidenced by the low MSE value of 0.032. The domain-specific fine-tuned BERT model showed a 2-4% performance improvement in semantic similarity analysis of webtoon synopses. Our proposed system successfully bridged the gap between visual and textual components by generating a unified latent space representation encompassing both artistic style and narrative elements.

These results underscore the importance of comprehensive analysis of both art style and synopsis in webtoon recommendation systems. Notably, the application of domain-specific learning and data augmentation techniques significantly contributed to the enhancement of the recommendation system's performance. The significance of this study lies in the following aspects: First, as personalized recommendations gain importance in the webtoon industry, our research presents the potential for developing more accurate and meaningful recommendation systems. Second, combining autoencoders and domain-specific BERT models introduces a novel methodology capable of effectively processing complex and diverse webtoon data. Last, our approach demonstrates the potential to overcome the limitations of existing methods in addressing cold start problems and handling long-tail distributions.

However, this study also has several limitations: One is that the dataset used in the experiments was limited to a single platform (Naver Webtoon), which may restrict the generalizability of the results. Another is that the lack of long-term analysis of user feedback and interaction data makes it challenging to assess the system's sustained performance.

For future research directions, we propose the following considerations: Incorporating data from various webtoon platforms to enhance the model's generalization capabilities. Developing dynamic models that reflect long-term changes in user preferences and webtoon trends. Exploring ways to improve model performance by considering additional webtoon elements (e.g., author style, serialization schedule, user reviews). Developing algorithms that take into account privacy protection and ethical recommendations.

In conclusion, this study presents a novel methodology for improving the performance of webtoon recommendation systems. This methodology is expected to contribute to advancing the webtoon industry and enhancing user experience. Future research can address this study's limitations and develop more advanced recommendation systems based on the proposed directions.

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