Visual Attributes of Thumbnails in Predicting YouTube Brand Channel Views in the Marketing Digitalization Era

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***Abstract*— Digitalization has shaped the relationships among companies, consumers, and social participants with the advancements of digital technology. As a result, companies are increasingly adopting and integrating the YouTube system for content dissemination and engagement with their customers and stakeholders. This study proposes a prediction model that analyzes 16 278 image datasets collected from 137 brand channels' videos with over 100 000 views, generated before September 26, 2022. Using the dataset, we analyze the factors affecting the number of content views of brand channels and construct a view prediction model. This study finds that the characteristics of the thumbnail image, offline top brand characteristics, and channel size (number of subscribers and number of channel videos) significantly influence YouTube's online channel views. The results of this study provide a strategy for brands to communicate more actively with stakeholders through the YouTube system.**

***Index Terms*— Brand channel, branded content, digital governance, digital marketing, image analysis, machine learning, thumbnail, YouTube system.**

I. Introduction

THE advancement of digital technology has created sustainable social structures that enable interactive engagement. This transformation causes socio-cultural change and facilitates mutual influence among corporations, customers, and social participants in the digital nation [1]. The need for developing a governance framework that comprehensively addresses factors involving stakeholders is emerging to ensure the sustainability of a digital nation [2].

At the focal point of this transformative process, characterized by user-driven innovation and value creation, lies the YouTube system, a prominent social media video-sharing platform. YouTube presents a distinct governance framework that allows channel owners to engage in communication, direction, and control, not only with their existing customers but also with potential new customers and various stakeholders (see Fig. 1). As of 2022, YouTube is utilized by approximately 33.1% of the global population, and its influence extends to 89.7% of the total population in South Korea [3]. Based on this influence, not only individual creators but also brands and governments operate their own YouTube channels to engage with people. According to Interbrand's 2017 report on the world's top 100 companies, brands such as Apple, Google, Coca-Cola, and Disney have an average of 3.13 YouTube channels [4]. Also, in South Korea, 208 out of the 251 local governments operate their own YouTube channels to engage with residents and tourists. Government organizations such as the Korea Tourism Organization also utilize the YouTube platform to promote South Korea.

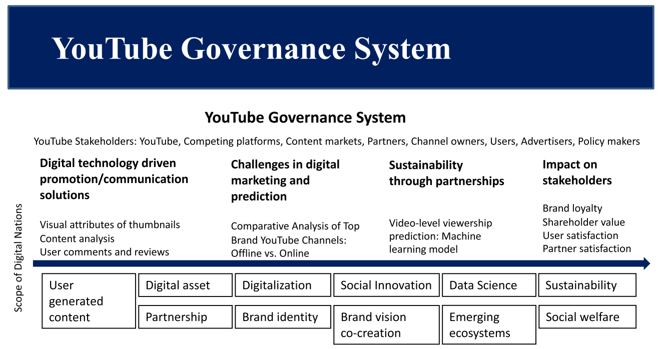

Fig. 1. YouTube governance system in the scope of a digital nation.

In the previous studies, the social function and role of YouTube as an online platform are being discussed as a digital medium [5], community [6], and role as an advertising medium [7]. Moreover, prior research has emphasized the significant implications of the YouTube system for stakeholder governance [8], [9]. By establishing online forums, YouTube effectively facilitates conflict resolution, negotiation, and communication among diverse stakeholders, including users, partners, and channel owners. As an independent platform that mediates hierarchical relationships, YouTube enables companies and brands to assume the role of custodians for these stakeholders. It also provides a platform for developing strategies that promote shared social interests and contributes to the overall well-being of stakeholders [10], all within the framework of their respective brands. For this reason, brands have started building structures to communicate with customers using the YouTube platform with their own channels.

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Global spending on digital advertising, including YouTube channel operation and content creation, was tallied at U.S. \$521.02 billion in 2021, with spending expected to reach U.S. \$876 billion by 2026 [11]. In the case of the Republic of Korea, digital advertising expenditure was tallied at U.S. \$5.92 billion 430 in 2021 [12].

The brands produce YouTube content for a variety of purposes, including entertainment, vision sharing, communication, trends, customization, and word-of-mouth [13]. In South Korea, the number of brands that open, operate, and manage YouTube channels directly for active communication with customers has also increased rapidly. Digitalization has transformed the marketing industry, in which customers have moved beyond their previous role as passive market participants to play a central role in driving corporate innovation by actively contributing and participating in the co-creation of products, services, and brand experiences [14].

Brands have recognized the potential of socially engaging storytelling as a powerful tool to reinforce their social value and foster stronger brand loyalty among stakeholders [15]. One notable example is the web drama "Whale Dust" produced and distributed by Samsung Electronics, Seoul, South Korea, on their YouTube channel. "Whale Dust" is a science fiction drama set in the year 2053, depicting a world where the rise of particulate matter causes environmental and societal devastation. Through this drama, Samsung Electronics communicates a message to viewers about the potential of advanced technologies, including artificial intelligence, to enhance people's lives and foster a compassionate society [16]. The drama effectively incorporates current environmental issues, such as particulate matter, to generate empathy among the viewers. The reason for its success is that it eliminated the direct exposure of the brand to web dramas to reduce consumer rejection and naturally communicate with viewers about the brand's vision through storytelling. As a result, "Whale Dust" received a significantly positive response compared to other preexisting branded content on the Samsung Electronics channel, amassing an impressive 7.5 million YouTube views within the initial 30-day period after its release.

In other cases, the social image of the brand is redefined, and the market is spread through the content co-creation process directly with their stakeholders. The "Ydrip Cinema" campaign, produced by KT, Seoul, South Korea, one of the South Korea's top three telecommunications companies, is a campaign that continues the story of content with viewers' comments. Marketers at KT thought that if customers could participate directly in the brand channel, they would feel curious and familiar with the brand without much information. It made a success and the average number of views on the channel at the time of uploading the campaign video was 810 000, but within two weeks of posting the campaign video, each video in the series had about 2.4 million views [17].

As the number of users on the YouTube platform continues to grow and the volume of content expands, it is important to note that not all video marketing activities conducted through brand channels are successful in effectively engaging with customers. Merely operating a YouTube channel and distributing content do not guarantee capturing the attention of stakeholders [18].

Attempts to increase the brand's market value and market share by utilizing digital technology are continued, but the competition to secure limited stakeholder interest is intensifying. According to statistics released by creator content management platform PEX, 90% of YouTube videos from 2018 to 2019 had less than 1000 views, and in 2019, 0.77% of all videos had severe polarization, accounting for 82.83% of all views [19]. In addition, since the success of the content can be determined after the content is uploaded, it is difficult to determine in advance whether stakeholders will choose the content. Therefore, with the digitalization of marketing, brands must create opportunities for communication by producing and distributing content that stakeholders can actively choose themselves.

This article measures the performance of social innovation (SI) in the context of digitalization by proposing the view count of content on YouTube channels operated by brands as a communication metric for brand and stakeholder engagement. Additionally, it aims to contribute to identifying attributes of brand content that are preferred by users within the digital governance system. By employing content attributes analysis, brands can effectively secure, communicate, and share their social vision and digital brand identity, ultimately maximizing social value. The goal is to enhance our understanding of how brands can align their content with user preferences, thus achieving stronger engagement and positive outcomes within the digital governance framework.

II. Related Work

A. SI and Stakeholder Value

An SI creates value by generating "new solutions for sustainable, legitimate social problems that go beyond individuals and belong to society as a whole" [20]. The development of digital technology has resulted in various innovations in the marketing industry, affecting the way brands communicate with their customers [21]. Through digital technology, brands can reach a wide range of customers on the internet without limitations of time and place, expanding their communication beyond specific customer groups and situations. In addition, active brands in the digital environment can increase brand awareness and loyalty by being shared and disseminated through customers, as customers become co-creators of brand innovation values [22].

The digitalization-driven SI has become a new opportunity for businesses to redefine the value of customers. Kumar et al. [23] conducted research to prevent the underestimation of customer engagement value (CEV) by proposing four components: customer lifetime value, customer referral value, customer influencer value, and customer knowledge value, to measure CEV beyond transactional-based assessment. Weinberg and Berger [24] proposed the concept of "Connected Customer Lifetime Value," which includes customers who are influenced by other customers' purchases, as well as those who directly purchase products/services since social media has enabled customers to connect.

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With the redefinition of customer value, research has emerged exploring the influence of customers as stakeholders on the governance structure of businesses. Broekhuizen et al. [4] define customers as co-creators of corporate value and propose a broad range of stakeholders, suggesting a business model for digital transformation and digital accountability to develop new digital business models. Edinger-Schons et al. [25] argue that customers should have the same right to co-decide how the company allocates its resources as every other member of the stakeholder network and propose a theoretical understanding of stakeholder democracy based on mutual communication, while also providing implications for management practices.

B. Predicting Videos Popularity

Along with the rapid growth of YouTube users and content, research on predicting the popularity of YouTube content has been actively conducted. Hoiles et al. [26] investigated the sensitivity of video meta-level features on video views using various machine learning methods and found that the number of views on the day of video upload, channel subscribers, the color contrast of thumbnail images, Google Trend keywords, the number of video keywords, video category, length of video title, and the number of uppercase letters in the video title are important meta-level features. Yen-Liang and Chia-Ling [27] created a Bag-REPTree meta classifier model including five base classifiers (Naive Bayes, support vector machine (SVM), logistic regression, neural network, and decision tree) to predict the future views of videos using eight initial data variables (related YouTube recommended videos, YouTube channel, video keywords, video title, video tags, video description, the number of video comments, and the number of channel subscribers). Kharkar and Ritvik [28] identified that the video attributes affecting the growth pattern of video views are the video upload period, length of the video title, and representative color of the thumbnail image. Based on these attributes, they created a model to predict the potential growth of views before the video is uploaded [28].

C. Brand Channel

YouTube brand channels are channels operated by brands to create and distribute branded content. In the context of this study, branded content refers to videos that are sponsored or produced by the brand and are uploaded to these brand channels [29]. What sets YouTube brand channels apart from traditional media platforms is their incorporation of user-generated content (UGC). Customers can collect brand content, replicate it for wider distribution, and share various opinions on the content, enabling continuous interaction. Through this interaction, brands can communicate with customers and create customer-tailored content [30], [31], [32], [33].

The toy manufacturer LEGO, Enfield, CT, USA, has the most popular brand channel on YouTube. As of 2021, the channel has recorded over 10.04 billion video views and has grown into a channel with more than 15.5 million subscribers as of January 2023 [34]. Samsung has the largest brand channel in South Korea, with a total of 27.1 million video views and 6.28 million subscribers.

Fig. 2. Thumbnail of Samsung Electronics' web drama "Whale Dust.".

As many brands expand their marketing activities through YouTube brand channels, related studies are beginning to emerge. Grant et al. [35] discovered that customers who viewed branded content uploaded to brand channels ultimately increased their liking for the brand and contributed to an increase in brand equity. Wang and Chan-Olmsted [36] explored how brands use YouTube brand channels for content marketing by examining the four psychological aspects (interaction, attention, emotion, and cognition) that are important when customers participate in marketing and revealed that a brand's ability to use YouTube, marketing budget, and product differentiation is important for developing brand strategies. Jeongi et al. [37] analyzed customer reactions to brand channel content by identifying current trends and characteristics of each type of content and revealed that message strategies and tactics vary depending on the product group, and that video length affects customer viewing behavior.

D. YouTube Thumbnail

The YouTube thumbnail is an image created by summarizing the content of the video and adding visual effects, as shown in Fig. 2. It is an image that allows users to obtain basic information about the video before selecting the content.

As the popularity of YouTube has soared, there has been a significant increase in the number of videos uploaded to the platform. To capture users' attention and provide a summary of the video content, video creators have started to put effort into designing visually appealing thumbnails. For this reason, research on thumbnails is actively underway. Zhao et al. [38] revealed that thumbnail images have the effect of inducing viewers to watch by allowing potential viewers to intuitively understand and become interested in video content through the study of visual and text elements of thumbnail images. Koh and Cui [39] collected 38 popular brand channels from four industries to explore the relationship between visual attributes of thumbnails and video views and found that too many objects in thumbnail images can hinder information transmission. Trzciński and Rokita [18] created a model that can predict popularity before video upload by using not only video characteristics such as video length and the number of frames but also visual characteristics such as object complexity and scene dynamics of thumbnail images, using Gaussian radial basis functions with support vector regression. Gupta et al. [40] analyzed the similarity with Google's top trend keywords by detecting the text of thumbnail images through the PyTeseract optical character recognition (OCR) model and creating a model that predicts the ranking of videos along with video characteristics.

The purpose of this study is to develop a model for predicting the number of views on YouTube brand channel content, which represents the degree of communication between the brand and the customer. To examine the relationship between the characteristics of the channel and video, as well as the characteristics of the brand and the visual elements of the thumbnail, we propose four types of representative thumbnail images for Korean YouTube brand channels. Based on the entire thumbnail images collected, we proposed four types of thumbnail images to include the visual properties of the thumbnail image in the prediction model, in addition to the video characteristics. While Hoiles et al. [26] and Yen-Liang and Chia-Ling [27] constructed prediction models by collecting channel and video characteristics for predicting YouTube video views, thumbnail image-related attributes were not applied to the models. On the other hand, Kharkar and Ritvik [28], Koh and Cui [39], and Gupta et al. [40] constructed prediction models including visual properties of thumbnail images, but they simply applied the color of the image, or the text included in the image to create the model. Therefore, in this study, we referred to Trzciński and Rokita's [18] object detection method for thumbnail images to distinguish the visual properties of the four types of thumbnail images previously identified and identified visual properties such as whether the person, text, and graphic objects were detected, and the complexity of the objects detected in the image.

Furthermore, this study goes beyond previous research by incorporating brand characteristics. Data on 137 brands operating YouTube channels were collected, regardless of their brand awareness or industry. Previous studies on YouTube brand channels or branded content, including [35], [36], [37], and [39], focused on high-awareness brand channels offline, successfully performing branded content, or top brands in specific industries. However, these studies ignored brand characteristics such as brand awareness or industry when analyzing brand channels. Therefore, we collected data on all videos of brands operating YouTube channels. Brand awareness was classified based on whether the brand was ranked in the top offline brand statistics website, and the brand industry was classified into similar industry categories and then dummy coded and applied to the model. A total of 11 industry categories were introduced to classify the brands.

The proposed prediction model in this study integrates the characteristics of YouTube brand channels and videos, brand characteristics, and visual properties of thumbnail images to predict the number of views before the video is uploaded. In [27], future video views are predicted based on early data after the video is uploaded. Kharkar and Ritvik's [28] study and Trzciński and Rokita's [18] study have models that can predict the number of views before the video is uploaded, but they only consider video attributes or predict views by considering both video and thumbnail visual properties, so they do not take into account channel characteristics. In particular, since this study focuses on brand channels engaged in marketing activities through the YouTube platform, a prediction model that includes brand characteristics is necessary. Consequently, the proposed prediction model in this study was built by integrating all the characteristics.

The results of this study can provide efficient channel operation and video production strategies for brands that carry out marketing activities on the YouTube platform. This study reveals that brand awareness has a significant impact on views. Therefore, brands should maintain continuous communication with customers not only through offline sales of products and services but also through YouTube channels and content. During this process, companies need to share their vision and engage with potential customers.

Finally, this study proposes guidelines for operating channels and designing thumbnail images that can increase video views. Identifying the characteristics that play an important role in channel operation and video production can provide direction that brands to operate their channels and plan content focusing on these features. Also, the model was proposed to predict views by considering the visual attributes of thumbnail images, such as colorfulness, brightness, object recognition, and object complexity. Brands can design thumbnail images more effectively by identifying the key visual properties that influence views, rather than relying on the automatic images generated by YouTube when creating their own thumbnail images.

To summarize, this study provides several contributions, summarized as follows.

1) This study suggests that YouTube governance system functions as a vehicle for companies to act as custodians of various stakeholders, enabling them to develop strategies that promote shared social interests and enhance their digital brand identity.
2) This study proposes the use of YouTube brand channel views as a valuable indicator of social performance in brand marketing. It recognizes that these views are a result of the dynamic communication and interaction between brands and stakeholders. By analyzing the promotional metrics of 137 offline and online branded content-operating YouTube channels in South Korea, this article examines the effects of digital technology on the marketing industry.
3) Based on the collected data, this study classifies thumbnail images of Korean brand channel contents into four categories. By focusing on the relationship between deliberately designed thumbnails and the corresponding views, this article investigates the significance of visual elements within these thumbnails. Rather than relying on automatically generated images, this analysis sheds light on the crucial role of purposefully crafted thumbnails in attracting viewership.
4) As an indicator that reflects user-driven market value about the brand, content views can be predicted before uploading a video. By leveraging this predictive capability, valuable guidelines can be provided to brands, encompassing channel operation and video production, from the content creation stage to the subsequent upload process on the YouTube platform. These guidelines enable brands to strategically optimize their content

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TABLE I
COLLECTED VARIABLES

Variable	Variable Name	Description
Brand Channels / Branded Video Elements	views	Video views (dependent variable)
	title	Title of the video
	duration	Video upload period (based on 2022.9.26)
	video_len	The length of the video
	channel	YouTube channel where the video was uploaded
	subscribers	YouTube channel subscribers
	video_num	Number of videos on the YouTube channel
	c_mean_views	The average views per video on the YouTube channel
	c_sum_views	The total views of the YouTube channel
Visual Attribute Factors of Thumbnail	R	The red value of the thumbnail image in the RGB color model
	G	The green value of the thumbnail image in the RGB color model
	B	The blue value of the thumbnail image in the RGB color model
	image_tag	Objects detected in each thumbnail image with tag confidence of 0.8 or higher among the explored objects
	person	Whether the thumbnail image includes people or not. If a person is detected, it is marked as 1, and if not detected, it is marked as 0
	text	Presence of text in the thumbnail image. If text is detected, the value is 1, and if not detected, the value is 0
	graphics	Whether the thumbnail image contains graphic effects. If a graphic effect is detected in the thumbnail image, it is 1; otherwise, it is 0
	category_tag	Extract the top 5 objects with the highest tag confidence for each category, excluding person, text, and graphics

to maximize their viewership potential and effectively engage with their target audience.

III. Data Preparation

A. Data Collection

For this study, we collected 156 channels in the "Company/Official" category provided by the YouTube analysis site "YouTube Ranking." Among them, we collected data for 137 channels excluding three public institution channels. The dataset comprises 115 470 videos in total. From these videos, a final dataset for modeling was constructed, consisting of 16 278 videos that have garnered over 100 000 views. The main variables of the collected data are shown in Table I.

Brand channels, branded content-related data, and thumbnail images were collected using the YouTube application programming interface (API) and the pytube library in Python.

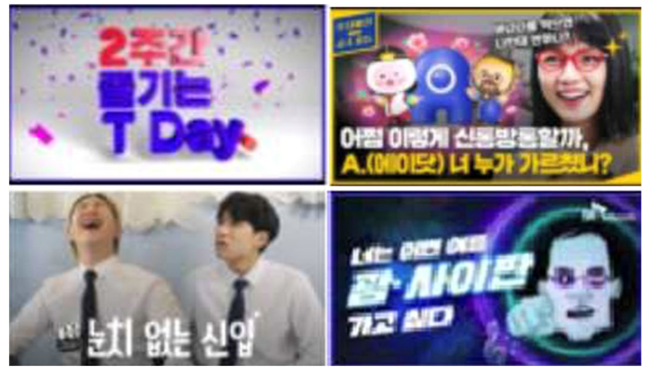

Fig. 3. Types of brand channel video thumbnail on YouTube.

TABLE II
DERIVED VARIABLES

Variable	Variable Name	Description
Brand Channels / Branded Video Elements	category	The category of the YouTube channel
	ranking	Whether the operating brand of the YouTube channel has been included in the top rankings offline, with a value of 1 for those that have been included and 0 for those that have not
Visual Attribute Factors of Thumbnail	Colorfulness	The hue of the thumbnail image
	brightness	The brightness of the thumbnail image
	object complexity	Complexity of each thumbnail image based on the Image_tag variable
	element complexity	The number of each thumbnail element based on the Image_tag variable

The "duration" variable was calculated in days from the date of upload to the data collection date of September 26, 2022. To analyze thumbnail images, the collected data were classified into four types, as shown in Fig. 3.

The first type encompasses an image with simple text containing basic information about the content. The second type applies graphic effects to illustrations and text. The third type involves text with graphic effects. The last type combines graphic effects for people/objects with accompanying text.

Using Python's Pillow library, the R, G, and B characteristics of the thumbnail images were collected. In addition, the CV library of Microsoft Azure was used to explore the objects in the images, and variables indicating the presence of people, text, and graphics were created.

B. Multipart Figures

The collected data were utilized to generate a range of derived variables, as shown in Table II.

1) Brand Channel: To differentiate brands that operate brand channels and are featured in the top offline rankings from those that are not, a ranking variable was created. The variable was established using the top offline ranking data for 2021, released by brand statistics analysis sites "Brandstock" and "Interbrand." In this variable, a value of 1 indicates that the

TABLE III
OFFLINE TOP 100 BRAND CHANNELS VERSUS ONLINE BRAND CHANNELS CATEGORY CHARACTERISTICS

YouTube Channel Category # of Obs.	Offline Top 100 Brand Channels (30 Brands)	Online Brand Channels (120 Brands)
Number of videos	5249	11029
Arts & Entertainment	221	4088
Autos & Vehicles	572	0
Beauty	36	851
Computers & Electronics	832	591
Fashion	35	1027
Finance	626	300
Food & Drink	754	2684
Games	444	1081
Internet & Telecom	1569	0
People & Society	0	183
Shopping	160	224

brand is included in the top 100 offline rankings, indicating a high level of offline brand awareness, whereas a value of 0 indicates that the brand is not included in the ranking, indicating relatively lower offline brand awareness. We also created a "category" variable based on the top-level vertical provided by YouTube-8M to reflect the industry characteristics of each brand in the view count prediction. This variable classified the brands into a total of 11 categories based on their industry characteristics and divided them into dummy variables for use in the model. The 11 dummy-coded category functions are shown in Table III.

2) Thumbnail: Using the Pillow library in Python, we derived the variables "brightness" and "colorfulness" from the obtained R, G, and B values. These variables represent the brightness and colorfulness of thumbnail images. Furthermore, the "object_complexity" variable was determined using the image_tag variable, taking into account the number of objects detected in each thumbnail image. This variable serves as a measure of image composition complexity. Similarly, the "element complexity" variable was created based on the category_tag variable, considering the number of category-related objects identified in each thumbnail image to assess image composition complexity.

C. Data Statistics

The descriptive statistics for the main variables, including the dependent variable "views," are shown in Table IV.

In Fig. 4, the probability density graphs illustrate the differences in the main variables of the view prediction model depending on whether a brand is included in the offline top ranking or not. The graph shows that brands included in the offline top ranking tend to have higher views. Additionally, the brightness and colorfulness of the thumbnail images are slightly skewed to the right for these brands, indicating that they design thumbnail images with more vivid and brighter colors. On the other hand, the subscriber count, which represents the channel size, is more polarized for brands that do not be included in the offline top ranking. Moreover, the number of video uploads per channel is skewed to the right for these brands, indicating that they upload more videos than brands included in the offline top ranking.

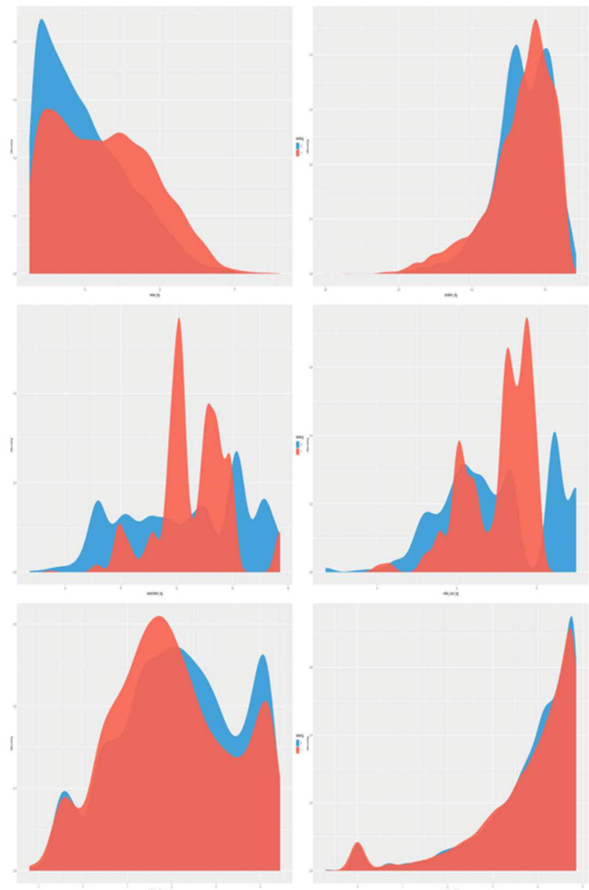

Fig. 4. Comparison of offline top 100 channels (red) versus online brand channels (blue)_views, duration, colorfulness, brightness, subscribers, and video_num.

IV. RESULTS

A. Methodology

This study selected five machine learning algorithms for prediction: polynomial linear regression (LR) for regression modeling (multivariate LR), SVM for nonprobabilistic LR modeling (SVM), ensemble-based tree modeling using bagging, random forest (RF), boosting-based models, XGBoost (XGB), and LightGBM.

In regression analysis, the dependent variable is represented by a linear combination of a set of regression-independent variables, parameters, and random errors [41]. However, due to its limited learnable relationships and tendency to oversimplify complex realities, it is often not recommended for predictive analysis [42]. Therefore, to deal with nonlinear relationships, the SVM model has emerged. SVM is used primarily for regression analysis and classification and is an algorithm that can be used for both linear and nonlinear relationships. It has the advantage of identifying fewer parameters for the model in a way that does not require the range of prior information or heuristic assumptions required by some previous techniques [43].

Decision trees divide a dataset according to a criterion that maximizes the separation of the dataset [44]. The tree structure is suitable for understanding the interaction between data features. However, decision trees cannot efficiently handle linear relationships. Hence, for more complex tasks, single-model ensembles have emerged, and ensemble techniques such as bagging and boosting have been used [45], [46]. The RF algorithm is a representative model with bagging applied to prevent overfitting problems that can occur in decision tree-based models [47]. The XGB algorithm and the LightGBM algorithm are models with boosting applied. The XGB algorithm provides a parallel tree boosting by weighting the errors of prediction models and sequentially reflecting those weights in the next learning model to create a strong prediction model [48]. The LightGBM algorithm provides a parallel tree boosting while using the leafwise method instead of the levelwise method to create a model quickly with minimal memory and demonstrates higher performance than algorithms of other boosting methods. However, the leafwise method is vulnerable to overfitting when the number of data to be trained is small [49].

Stepwise regression was used to select independent variables for predicting the number of views of YouTube brand channel videos. Stepwise regression is a model that selects statistically significant independent variables that are most helpful in explaining the dependent variable, after selecting all available variables as independent variables [50]. Therefore, this model was used to select the following six variables as independent variables with high statistical significance to the dependent variable: ranking, subscribers, colorfulness, brightness, video_num, and duration.

For this study, out of 16 278 collected data, 10 660 data until 2020 were selected as train data, and 5618 data from 2021 to 2022 were selected as test data as shown in Table V. Instead of randomly dividing the data into train and test data, the data were divided based on the year when the video was uploaded to study the present with past data and predict the future using the model.

To achieve optimal performance for each model, parameter selection was performed, and the optimal parameter values were calculated through hyperparameter tuning. The models used to predict the number of views include polynomial LR for regression models, SVMs for nonprobabilistic LR models, and ensemble-based tree models such as RF with bagging, XGB with boosting, and LightGBM with boosting.

B. Model Performance Evaluation

We used mean absolute percentage error (MAPE, %) to compare the performance of the models

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\frac{|A_i - F_i|}{A_i}. \quad (1)$$

Table VI shows the results of the prediction performance for each algorithm in terms of MAPE (%), and the overall MAPE for all models was less than 5%.

According to the results of the prediction performance for each algorithm shown in Table VI, the SVM model showed the best prediction performance among the regression models, and it also showed the best performance even when decision tree-based models were included. Among the decision tree-based models, the XGB and LightGBM models, which apply boosting techniques, showed better performance than the bagging-based RF model.

TABLE IV
DESCRIPTIVE STATISTICS

Variable	Mean	Median	S.D	Min	Max
views (thousands)	1260	418	2692	100	81506
duration	1230	942	972	1	5197
video_len	246.5	79	665.1	5	16296
Subscribers (thousands)	954	280	1537	0.826	6670
video_num	2015.78	1279	2208.88	15	7991
c_mean_views (thousands)	32.33	24.19	36.17	0.0618	205.9
c_sum_views (millions)	35.28	10.10	50.79	0.0637	153
colorfulness	13.59	4.56	20.03	0	85
brightness	61.68	59.47	41.92	0	128
object complexity	0.36	0.33	0.27	0	1.95
element complexity	1.169	1	0.7711	0	3

TABLE V
TRAIN DATA/TEST DATA

Train Data	Videos uploaded until 2020
Test Data	Videos uploaded from 2021 to September 26, 2022

TABLE VI
RESULTS OF THE PREDICTION

		LR	*SVM*	*RF*	*XGB*	*LightGBM*
MAPE (%)	Train	3.01	0.952	0.98	1.99	2.534
	Test	4.18	1.055	4.806	2.763	2.956

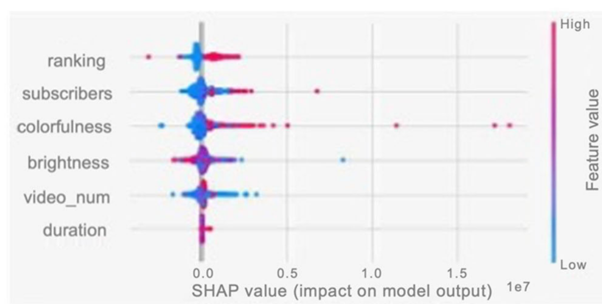

Fig. 5. Shapley value of XGB model.

The findings from the Shapley value analysis, as depicted in Figs. 5 and 6, reveal the significant variables that contributed to the prediction process. Notably, the variable indicating whether a brand was included in the top offline ranking emerged as the most influential factor. This variable's prominence underscores the importance of offline brand recognition in shaping the viewership dynamics on YouTube. Furthermore, the research findings indicate that there is a positive correlation between the number of subscribers and the number of videos on a channel, and the higher these numbers are, the higher the viewership of the content. Thumbnail features such as colorfulness and brightness have a strong impact on the viewer's image selection.

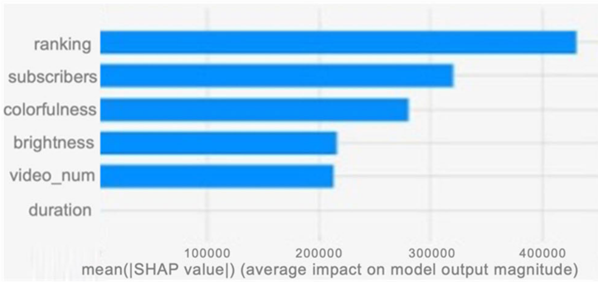

Fig. 6. Average Shapley value of XGB model.

V. Conclusion

Digitalization has revolutionized online marketing by fostering user and stakeholder engagement in the communication process. The YouTube system has established a framework that empowers users to create, distribute, and optimize their own videos. This framework enables brands to generate and disseminate content relevant to their brand, engage with stakeholders, and collaboratively create value. The emergence of this digital governance structure has become a crucial factor in addressing diverse issues within the contemporary marketing industry.

This article analyzed factors affecting the number of views on YouTube brand channels by maximizing the visual effect of thumbnails as a platform for various brand stakeholders and organizations to share their vision and co-produce videos. We found that whether a brand is included in the top rankings offline, the number of channel subscribers, brightness and colorfulness of thumbnail images, the number of videos on the channel, and the video upload period decisively affect the number of views.

In this article, we propose the utilization of the number of views as a metric to assess the level of communication between brands and customers. To accomplish this objective, we develop a machine learning-based model that incorporates the visual characteristics of YouTube video thumbnails, along with the attributes of brand channels and videos, and brand awareness, to forecast the expected number of views. By enabling the anticipation of views before content upload, this model offers brands valuable guidelines for optimizing content creation and managing their YouTube channels effectively, thus facilitating continuous communication with customers in alignment with their preferences and choices. To provide specific content and thumbnail image creation guidelines, additional research is necessary.

First, additional data collection is necessary. The data used in this study were based on Korean YouTube data, and while it can provide guidelines for Korean marketing strategies, it does not encompass the characteristics of brand channels worldwide. Therefore, data collection and comparative analysis of brand channels in various countries are necessary.

Second, a specific comparative analysis of thumbnail image objects and characteristics is required. This study found that the brightness and colorfulness of thumbnails play an important role in views. However, we could not specify the exact degree of brightness and colorfulness that is most helpful for views. Therefore, conducting experiments with different thumbnail images for the same video can help determine which designs generate a more positive response from viewers.

Third, research on external factors such as marketing expenditure, operational personnel, and brand awareness is necessary for YouTube brand channel operations, as whether the brand has been included in the offline top rankings significantly affects views.

This study has uncovered a relationship between the visual elements of brand channels, videos, thumbnails, and the number of views. Given the increasing prominence of marketing activities on YouTube, we aim to offer valuable insights and assistance to brands involved in planning, producing, and distributing content, as well as to diverse stakeholders engaged in brand communication through the platform.

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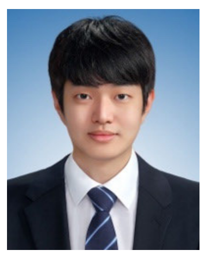

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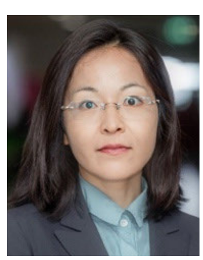

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