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Prediction of Online Video Advertising Inventory Based on TV Programs: A Deep Learning Approach

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ABSTRACT With the recent spread of digital content, patterns of media viewing have changed. This is especially true for programs formerly watched on TV but are now increasingly viewed through online videos. As more and more people watch online videos, the market for online video advertising is increasing. Including online video advertising, online advertising can be effective if advertisers and online service providers attract as many viewers as possible. In particular, service providers try to maximize their profits by efficiently selling advertising inventory, which indicates the volume of space available for advertisements. However, most of today's service providers use simple statistical applications to predict advertising inventory that leads to relatively inaccurate predictions. Therefore, this study aims to develop a model capable of accurately predicting advertising inventory and then validate the model. This study in predicting online video advertising inventory is based on using deep learning to analyze the raw data of online video channels and then comparing the results of these predictions with actual inventory, other results of machine learning techniques, and work-site method results. Using these techniques and approaches, future advertising inventory can be more accurately predicted. In addition, detailed strategies for the practice of online video advertising are suggested.

INDEX TERMS Advertising inventory, online video advertising, TV programs, deep learning, prediction.

I. INTRODUCTION

Due to the recent expansion of digital content, patterns of media viewing have changed. Although the ratings for TV viewership, the most traditional medium, have dropped significantly, the number of viewers of online videos based on various media has increased [1]. The number of total active users on YouTube per month is two billion [2], and they collectedly watch 1 billion hours of online videos per day [3]. This rapid growth and spread of online content have spurred changes in digital media that extend even to associated advertising [4]. Online advertisements have become the dominant medium in most countries, including U.K, China, and Canada, and U.S., a latecomer to the rising tide of online advertising but recently accounted for 54.2% of total adverting spending. Global spending on online advertising will increase to $435.83 billion by 2021, which means that online advertising will account for nearly half of the global advertising market for the first time [5].

Online advertising conveys marketing messages to users via the Internet and it can deliver relevant messages to targeted consumers by analyzing website traffic [6]. Because people are now watching programs on various media they used to watch on TV, viewers have become interested in the online advertisements accompanying them. Online video advertising provided together with online video contents is classified into pre-roll, mid-roll, and post-roll according to placements [7]. Even though advertisers and online video service providers, the key operators of the online video advertising market, are connected, at the same time they share different goals. Advertisers want to reach as many people as possible, but the main goal of service providers is to maximize profits by efficiently selling advertising space. Here, the amount of advertising space available to sell to advertisers

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is called advertising inventory [8]. To satisfy both advertisers and service providers, it is important not only to expose advertisements to as many people as possible but also to sell advertising space efficiently by accurately predicting the amount of advertising inventory available.

Advertisements provided with online video channels of highly popular broadcasting programs are especially likely to gain increased exposure. Therefore, in their decisions to buy effective advertising space, advertisers must consider the popularity of any associated online video channels. In making their decisions, advertisers want to know how much exposure their advertising will get on specific channels. In response, advertising service providers predict and sell their advertising inventory based on online video channels. For these service providers, an accurate prediction of advertising inventory can increase revenue and profit [9]. In other words, increased revenue depends heavily on accurate predictions of advertising inventory.

According to the results of interviewing the Google advertising manager who is in charge of online advertising [10], the major service providers of online advertising usually calculate their final inventory predictions by averaging inventory of a channel over the past several months and analyzing seasonal trends. Currently, most service providers predict their inventory by using simple statistical applications which leads to relatively inaccurate predictions. Because they recognize that their predictions are unreliable, providers generally sell less amount of advertising inventory than the expected advertising inventory in order to lower risks. Therefore, more accurate cutting-edge analytical techniques are needed to predict advertising inventory from past data. The analytical techniques allow deriving superior insights from advancements in data (Gupta *et al.*, 2020). The recent online advertising field tends to use programmatic advertising as a new marketing technique applied to emerging technologies [11], [12]. Programmatic advertising has higher accuracy than the traditional model as it examines large amounts of data via the recently developed novel technique [12]–[15]. Ultimately, accurate predictions of advertising inventory by this advanced approach can benefit both advertisers and service providers.

The exposure of advertisements and the prediction of advertising inventory are important in online advertising. However, most previous studies have been about the effectiveness and impact of online advertising [16]–[21] and the motivation of behaviors toward online advertising [22], [23]. Rarely researchers have undertaken studies on the prediction of online advertising inventory by analyzing online video channels in terms of maximizing the effects of advertising. Therefore, this study is to develop a model to predict advertising inventory (i.e., the amount of advertising space available to sell to advertisers) based on online video channels and to suggest detailed strategies for the execution of online advertising. First, we analyzed 735,223 hours of data on advertising inventory from 36 channels and then developed the prediction model by applying a deep learning method. After developing the model, we evaluated its results with actual data. Finally, we compared the predicted inventory results with the results of other machine learning techniques and work-site methods. This overall approach will allow us to predict future advertising inventory for each online video channel and to suggest detailed strategies for advertising execution. This study is significant because our development of an online advertising inventory prediction model is through the use of a deep learning technique. In practice, it is meaningful in that it predicts TV program-based advertising inventory in online advertising and suggests strategies and plans for online advertising execution.

II. CONCEPTUAL BACKGROUND

A. ONLINE ADVERTISING

The widespread adoption of digital media means we have left an age dominated by the four traditional media types—TV, radio, newspapers, and magazines—and stepped into a new age of online digital content increasingly accessed via mobile devices [24]. Global expenditure on media continues to increase, and online advertising is currently the fastest-growing category [25]. The advertising market is also changing, driven especially by the shift in content from traditional media such as TV to the online environment. Online advertising, also called Internet advertising and digital advertising, provides advertising that uses Internet technologies [26]. Online videos, especially, facilitates people to efficiently absorb content with little effort. Therefore, online videos can be a dominant online advertising category among various online advertising categories.

Fig. 1 shows the process of online video advertising and traditional TV advertising. The advertising market is classified into advertisers and media, and the types of media have diversified since the advent of online advertising (i.e., online video advertising). In Fig. 1, the media on TV advertising represent the advertising space for TV, and the media at online video advertising represent the advertising space available on online video channels. Traditional TV advertisers and online video advertisers choose and buy advertising space through requests to their advertising agencies, a practice that has not changed. However, as the form of advertising has changed, the tasks of service providers have also changed. First, in traditional TV advertising, broadcasters or media representatives sell TV advertising slots to advertising agencies (advertisers). Here, the unit of advertising sales is the number of slots between TV programs. On the other hand, in online video advertising, service providers such as YouTube sell online advertising inventory to advertising agencies (advertisers) instead of to the content provider (i.e., broadcaster). The advertising sales unit is the amount of inventory in the content or channel. Therefore, it is important for service providers to sell this inventory effectively. In other words, they try to enhance their profits by selling advertising inventory based on accurate predictions of availability.

Online video is used and considered as an effective and popular form of advertising media [28]. ADvendio has

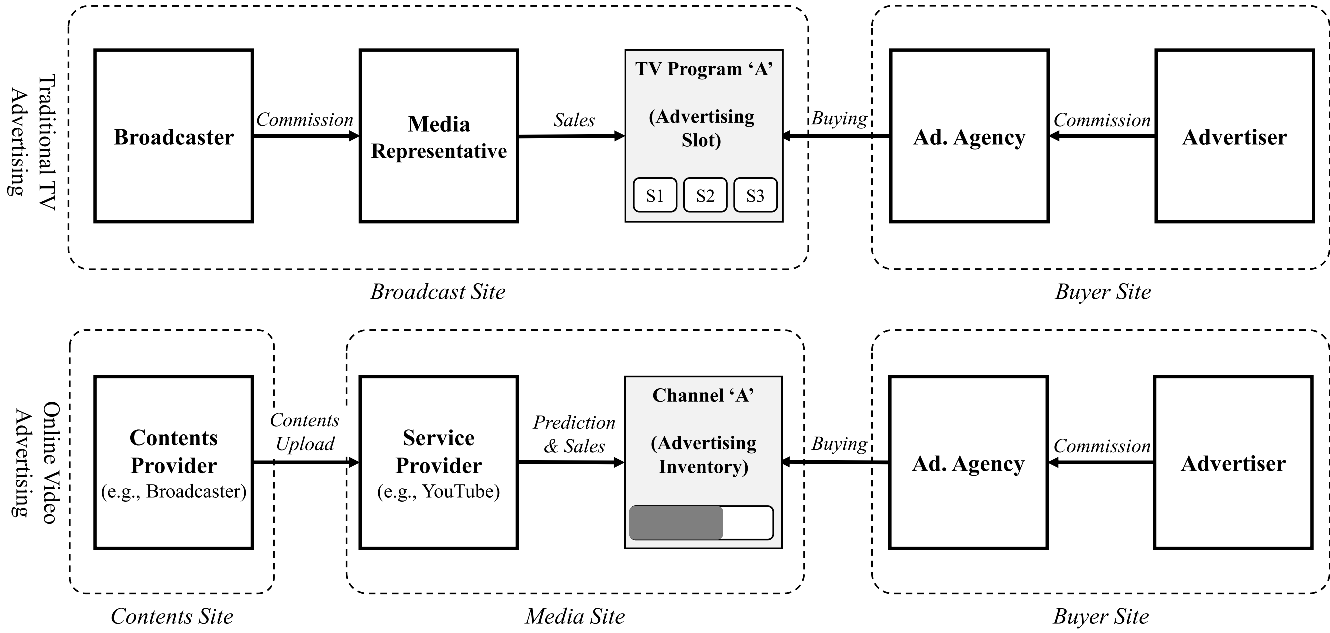

FIGURE 1. Process of traditional TV advertising and online video advertising.

predicted that spending on online video advertising will increase to $13.43 billion, constituting nearly two-thirds of nonsocial display advertising spending [27]. As consumption of online videos and online video advertising increases, the ability of advertising service providers to increase their profits hinges on accurate predictions of their online inventory. Our research in this study relies on deep learning techniques to arrive at a more accurate predictive technique to replace the use of simple statistical applications that are rarely reliable. We used the latest analytical approaches to develop an advertising inventory predictive model that is based on a deep learning technique that is used for predictive analysis in various fields. We then verified its predictive power by comparing its results with those of other machine learning techniques.

B. LITERATURE REVIEW

As interest and investment in online advertising increase, academic interest in this area also increases. Most of the previous studies on online advertising focused on the effects of online advertising and its motivations [16], [20], [21]. None was concerned with advertising inventory prediction, which is one main issue in the advertising market. Xiang *et al.* [29] conducted a study that proposed an advertising system using textual information and visual content to connect and provide advertisements most appropriate for online video. However, this study relied on an experimental method and did not use actual user data and predicted advertisements based on digital content [29].

Besides, prediction-related studies have been conducted in various fields such as broadcasting, television advertising, box offices, fashion retail, and traffic flow [30]–[35]. Table 1 shows the previous studies on prediction. Qu *et al.* [35] used a deep learning algorithm based on historical traffic data to predict daily long-term traffic flow. They adopted a deep neural network approach to forecast traffic flow and then evaluated its performance by using the mean absolute percentage error (MAPE) and charts [35]. Hwang *et al.* [28] applied classification-based machine learning techniques to predict customer revisits in the context of airline service [36]. Liu, Y., and Xie, T. [32] predicted box

TABLE 1. Previous studies related to the prediction.

Context	STUDY	Method	Content
Traffic	Qu et al. (2019)	Deep or machine learning	Forecasting daily long-term traffic flow
Airline service	Hwang et al. (2020)	Machine learning	Prediction of customer revisiting
Box office	Liu and Xie, (2019)	Deep or machine learning	Forecasting performance of films
Fashion retail	Loureiro et al. (2018)	Deep or machine learning	Forecasting sales in fashion retail
Broadcasting	Danaher et al. (2011)	Econometrics	Forecasting television ratings
Broadcasting	Napoli (2001)	Combination of Delphi and the Grass Roots	Forecasting error for new prime-time network television programs
(TV) Advertising	Bollapragada et al. (2008)	Exploratory analysis	Estimated demand for commercial television time

office performances of films by contrasting nine econometric and machine learning algorithms. The results showcased the advantage of machine learning algorithms in detecting irregular patterns, such as content performance forecasting [32]. Loureiro *et al.* [33] predicted fashion product sales by using five deep neural network algorithms and evaluated the performance of each algorithm. The results illustrate that a deep neural network yield excellent results for evaluative indicators (i.e., R^2, RMSE, MAPE, MAE, and MSE) [33].

Danaher *et al.* [23] and Napoli [26] used econometric and exploratory analysis to predict television ratings. Both studies explained the importance of TV in the advertising market and the prediction of TV ratings. The study by Danaher *et al.* especially demonstrated the financial impact of improved forecasts of TV ratings on the television industry [31]. Bollapragada *et al.* [30] proposed a predictive system for advertising demand to support a broadcaster's sales of on-air advertising inventory. The system adopted a combination of the Delphi method and the Grass Roots approach to estimate demand for commercial television time [30]. In these various fields, prediction related studies using forecasting models of deep neural networks were carried out. With the recent increase in investment in online advertising, accurately predicting the amount of advertising space that can be sold to advertisers has now become crucial. Research in this field, however, has not yet been conducted. Therefore, we used actual user data to predict advertising inventory based on online video channels and based on these results, proceeded to suggest a detailed strategy for the execution of online video advertising.

III. RESEARCH CONTEXT

For our study, we collected data on online TV channels with the help of S Service,[1] a pseudonym for South Korea's representative online video service. It provides online video services, such as broadcasting content, by establishing partnerships with major broadcasting companies. TV clips related to broadcasting programs account for 90% of its whole online video services. Each TV program has its own online TV channel and the playlist consists by the order of episodes. Approximately the five-minute TV clip consists of broadcasted video highlights and an online-exclusive video related to the TV program (see Fig. 2). The online-exclusive videos include backstage videos, interview videos, and no good (NG) videos. The highlights are edited, uploaded, and played for about five minutes, with actual run-time determined by the length of the TV broadcast.

S Service mainly sells online video advertisements to specific channels based on content targeting. It is similar to YouTube's reservation advertising [37], which predicts next month's inventory for each channel and then sells video advertising inventory equal to the predicted amount.

[1] For reasons of confidentiality, we will refer to this Korean video service by the pseudonym of S-service.

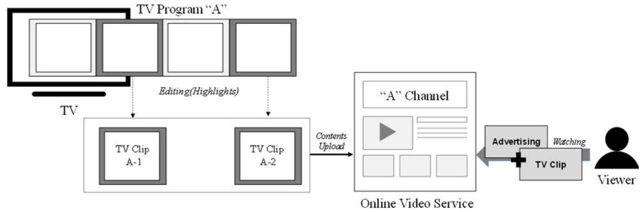

FIGURE 2. Relationship between a TV program and a channel.

S Service executive said in an interview that the issues of next month's TV programs (e.g., cancellations, guests, big events, etc.) are reviewed based on an average of the channel inventory over the last three months to determine the final inventory prediction. To ensure the stability of the sales environment, however, sales and marketing were conducted conservatively by pursuing sales of only 50% of the predicted amount. The reason for this conservatism is that each channel carries a cost per mile (CPM) unit price auction in an advertiser unit that is based on the predicted amount, and the number of winning advertising impressions must be guaranteed. Therefore, the advertising system determines the exposure of the winning advertising campaign by calculating its target amount per minute.

We collected from S Service the hourly data on advertising inventory by time zone from January 2017 to July 2019 for 50 channels with the highest inventory. From the 50, we used 36 channels for analysis after excluding channels that have not yet been released for three months and those that have had problems such as cancellation. The final number of extracted raw data cases was 735,223. Of the 36 channels, seven channels (19.4%) were opened after January 1, 2017. By genre, the highest number of channels was 19 (52.8%) entertainment channels, followed by 9 refinement channels (25.0%), 4 music channels (11.1%), and 4 news channels (11.1%). As of July 2019, there were 26 on-air channels (72.2%), seven online-exclusive channels (19.4%), and three closed channels (8.3%) according to the TV broadcast report. Fig. 3 shows the histogram of monthly inventory distribution by TV programs. The basic inventory statistics for the 36 programs in June 2019 were mean, 2,704,594; medium, 1,005,526; standard deviation (S.D), 3,186,916; minimum, 126,164; and maximum, 11,690,438 impressions.

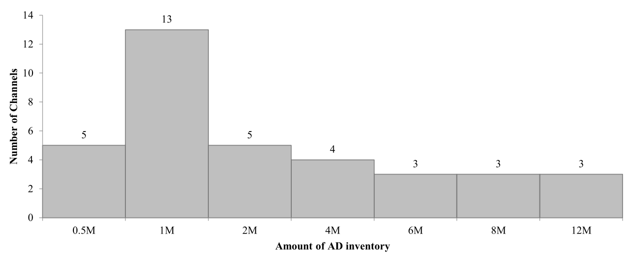

FIGURE 3. Advertising inventory of channels (TV programs).

IV. METHODOLOGY

This study uses the Long Short-Term Memory Networks (LSTM), which is a deep learning algorithm, to predict video advertising inventory by channel. The inventory for 36 channels in July 2019 was predicted, and the predicted value was estimated by a statistical method. We compared the values of predictions through LSTM with three other results; values predicted by S service, values predicted by other machine learning methods, and actual advertising inventory values.

A. LSTM ANALYSIS

LSTM analysis is a form of recurrent neural network (RNN) that allows the discovery of long-term dependencies in temporal data [38]. The RNN has the characteristic of effectively analyzing time-series information because the hidden layer value for the existing input stored inside the neural network is considered at the output of the next input value [39]. However, RNN has a structure that depends on past observations, so there is the problem of a vanishing gradient or a very large or exploding gradient [40]. Consequently, LSTM is suggested as an alternative to RNN because the RNN has a long bias and its sequence may be inefficient. Because online video advertising inventory is characterized by its time series dependency (i.e., future online video advertising inventory is influenced by past online advertising inventory), the LSTM technique is appropriate for the prediction.

The LSTM method uses a gate designed to accumulate information for a long time or forget previous information by replacing an internal node with a form called a memory cell [32], [33]. Each LSTM block consists of a memory cell, an input gate, a forget gate, and an output gate. Inside the LSTM, the information to be reflected in the memory device is determined through the input, forget, and output gates [42]. The output vector is recursively transited inside the LSTM. In this study, the output vector value corresponds to the advertising inventory for the next month.

B. RESEARCH PROCEDURE

The analytical procedure of this study is diagrammed, as in Fig. 4. (1) We collected hourly data on the advertising inventory data of 36 channels by time zone, and (2) min-max normalized the collected data. Input sequences were adjusted to the 0-1 range because overflows can be avoided in the calculation of LSTM through normalization [42]. (3) Normalized data were split into training data and test data from January 2017 to June 2019 and test data to July 2019. The predictive model, which was constructed through training data, was used to predict the hourly inventory for four weeks from July 1 to July 31, 2019. We also appended columns in time reverse order (t-1, t-2, $\cdots$ t-744) as variables. The LSTM analysis in Python's Keras package was used for the analysis.

The goal of the LSTM analysis was to select an optimal model because the performance of the model depends on the hyperparameter setting. (4) Various models are available for this optimal selection, and we applied k-fold cross-validation. This is a method of equally dividing the training data into k, using k-1 of the equally divided training data for training, and verifying the performance of the model using the remaining one data. The verification process is performed k times because there is verification data equal to as many times as the number is equally divided [43]. We applied 10-fold cross-validation to change the hyperparameter while determining the model with the lowest average of root mean square error (RMSE)—as calculated by k-fold cross-validation, but kept the data in temporal order (it called walk-forward validation test [44])—as the optimal model. Notably, we tested sigmoid, tanh, and rectified linear unit (ReLU) as the activation functions in the hidden layer. Next, root means square propagation (RMSProp), gradient descent (SGD), and adaptive moment estimation (ADAM) were tested as optimizers. This study adopted the mean absolute error (MAE) as the loss function to be minimized [45]. Among the suggested hyperparameter values, we decided on the hyperparameter values as shown in Table 2.

(5) The selected model was used to derive the predictions ($24h \times 31d = 744$) by time zone from July 1 to July 31, 2019, for each channel. Because the derived predictions were normalized, we predicted the advertising inventory by counting backward from the normalized values. The developed advertising inventory prediction model is presented in Fig. 5.

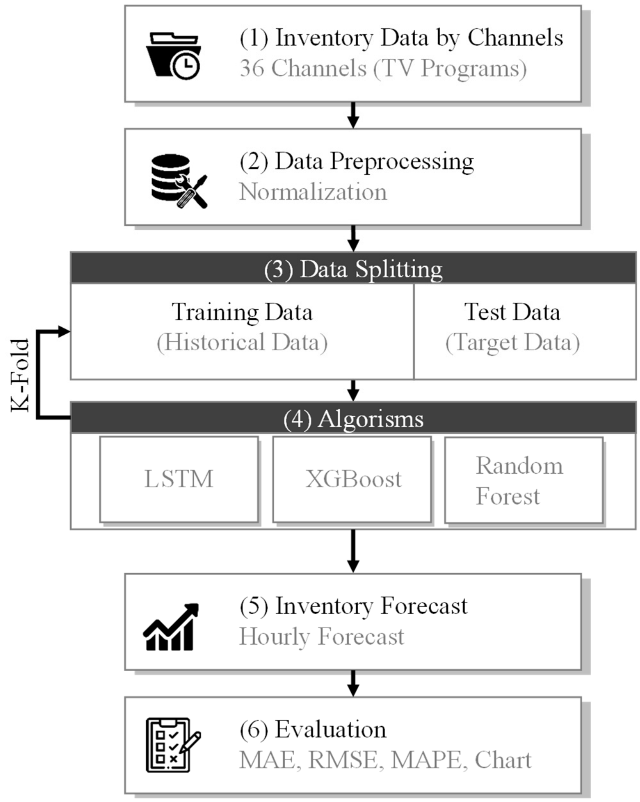

FIGURE 4. Research procedure[2].

[2]The source code is available at https://github.com/sundonam/Prediction-of-Online-Video-Advertising-Inventory-Based-on-TV-Programs

TABLE 2. Hyper-parameters for the proposed model.

Hyper-parameters	Description	Value
Window Size	Time unit for the LSTM algorithm to train	168 (7days)
Neuron	The number of neurons in a layer	100
Epochs	The number of times that the training dataset is shown to the network during training.	20
Batch	The number of patterns shown to the network before the weights are updated	12
Dropout	The dropout percentage between 0.0 and 0.9	0.3
Loss	The calculation of loss of prediction	MAE
Activation	The function to control the non-linearity of individual neurons.	Relu
Optimizer	The function to help train the model to minimize loss	ADAM

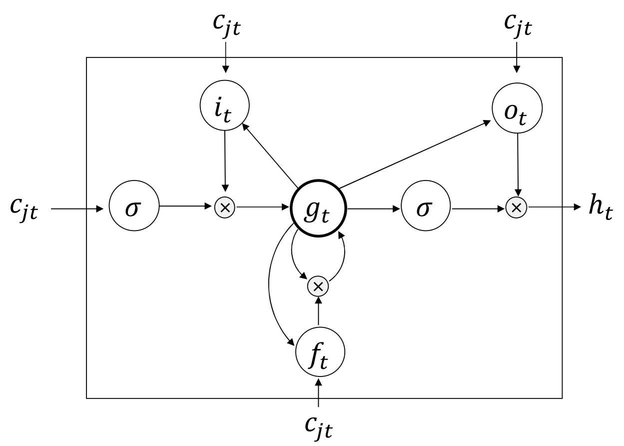

FIGURE 5. The architecture of the developed model [42].

Input: Hourly data on advertising inventory of trained data for channels, $c_{jt}(j = 1, 2, 3, \cdots, 36)$
Output: Hourly data on advertising inventory of test data (24 hours·31 days = 744)
1) WHILE the current RMSE is lower than the last RMSE
  DO
  FOR append columns in time reverse order (t-1, t-2, $\cdots$ t-744) for each channel j
  min-max standardized for advertising inventory data [Range: 0∼1]
FOR the transition function of LSTM equations (1)-(6)
  (1) $f_t = \sigma\left(W_f \cdot [h_{t-1}, C_{it}] + b_f\right)$
  (2) $i_t = \sigma\left(W_i \cdot [h_{t-1}, C_{it}] + b_i\right)$
  (3) $\tilde{g}_t = tanh\left(W_r \cdot [h_{t-1}, w_t] + b_r\right)$
  (4) $g_t = f_t \odot g_{t-1} + i_t \odot \tilde{g}_t$
  (5) $o_t = \sigma\left(W_o \cdot [h_{t-1}, C_{it}] + b_0\right)$
  (6) $h_t = o_t \odot tanh\left(g_t\right)$
  FOR find the optimal combination of hyperparameter for each channel j
    train the predictive model on 9 folds and compute predictions for the remaining fold
    calculate the RMSE between the predictive models
    store the combination of hyperparameters that result in the best RMSE score.
2) FOR LSTM algorithm execution based on optimal hyperparameter for each channel j
    Calculate the RMSE, MAPE, and MAE for each channel j
    Predict the advertising inventory by counting the normalized values backward
    Generate the plot charts between actual and predicted data

c_{jt} is hourly data on the advertising inventory of trained data for channel j.σ and $\odot$ are, respectively, a sigmoid function and element-wise multiplication. h_t is the output vector of the hidden layer at time t. b denotes the bias, and w denotes the weight matrix. (6) Finally, we evaluated the predictive results of each model.

C. EVALUATION

We used Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Root Mean Square Deviation (RMSE) to evaluate the model. We also analyzed and compared XGBoost and Random Forest, which are the other machine learning techniques, in order to verify the relative superiority of the model [46], [47]. The accuracy of the model is estimated in terms of the error sum, which is the difference between the predicted value and the actual value. The predictive model derives the estimated value Y for the dependent variable; the distance, as calculated by the absolute value, between the two values is defined as an error. Through this process, MAE can be derived. A lower MAE, MAPE, and RMSE value indicates higher accuracy in the prediction model.

V. RESULTS

A. DEVELOPED LSTM MODEL RESULTS

The results of the predicted advertising inventory for each channel based on the developed LSTM model are shown in Table 3. Its alignment was based on MAE, which was the sum of the differences between the predicted and actual inventory. In the prediction results of 36 channels in each time zone, the scope was shown as follows: MAE between 43.33 ∼ 6,450.03, MAPE between 17.2 ∼ 79.28, and RMSE between 57.97 ∼ 15,170.56. Here, the results of the evaluation indexes have such a wide scope because the relative error size naturally grows proportionately to the inventory size, which is the predicted dependent variable. Specifically, the mean evaluation results of the 36 channels could be considered a bit higher than the figure reached in the existing prediction-related research. This occurs because this study had numerous over-forecasts in which the predicted value of the advertising inventory of the channels in each time zone substantially exceeded the actual value [48].

Using LSTM, the predictive model developed in this study predicted satisfactory values of advertising inventory when compared to the corresponding actual advertising inventory

TABLE 3. Evaluation results of the developed LSTM model.

Channel Name	Genre	Airing	Actual Inventory (for July 2019)	LSTM Results MAE	MAPE	RMSE
Just happened	Entertainment	OFF	108,195	43.33	30.35	57.97
A Collection of Songs on TV	Entertainment	OFF	419,689	128.24	24.49	230.82
Manmulsang	Information	OFF	287,150	140.64	36.04	395.48
eNEWS24	News	OFF	408,620	177.98	29.97	286.16
King of Mask Singer Special	Entertainment	OFF	724,408	204.08	17.2	631.42
Ksintong	News	ON	240,437	244.85	67.45	915.23
Dongchimi	Entertainment	ON	443,455	261.42	48.61	385.22
Comedy Big League	Entertainment	ON	594,164	275.58	34.61	534.16
TalkTalk	Information	ON	1,083,767	323.35	20.54	678.21
Yard in the Morning	Information	ON	612,917	334.58	43.13	654.71
News Train	News	OFF	660,102	357.08	44.4	499.59
Battle Trip	Entertainment	ON	529,518	474.14	55.84	1,552.97
Miss Trot	Entertainment	OFF	1,010,026	484.03	41.17	649.58
Good Morning	Information	ON	681,913	484.89	42.77	1,374.90
Morning wide	Information	ON	860,054	525.9	50.32	1,080.26
Thumb King	Entertainment	ON	707,392	543.39	49.16	1,703.99
Body God	Entertainment	ON	933,470	583.28	52.03	1,017.37
Natural Person	Information	ON	1,017,741	756.73	52.18	2,012.33
2TV Live	Information	ON	1,002,691	757.77	56.3	1,683.16
Amazing News	News	OFF	870,076	764.77	79.28	2,132.69
TV Zoo	Information	ON	1,089,067	822.81	46.51	2,229.60
Baseball plus	Entertainment	OFF	1,540,826	1,070.44	63.07	1,640.81
Unanswered Questions	Information	ON	3,543,785	1,094.21	19.91	2,301.62
The Law of the Jungle	Entertainment	ON	2,199,586	1,186.59	35.72	2,752.54
Sketchbook	Music	ON	2,288,923	1,220.29	39.03	2,840.96
The Show	Music	ON	1,348,297	1,252.21	71.19	2,914.86
Cool Pick	Entertainment	OFF	2,440,329	2,113.88	71.93	4,035.22
Music Core	Music	ON	4,008,277	2,203.91	35.69	6,995.61
M COUNTDOWN	Music	ON	3,705,442	2,413.59	75.23	10,041.59
King of mask singer	Entertainment	ON	4,749,379	3,118.56	38.48	8,610.95
Running Man	Entertainment	ON	6,682,419	3,638.07	36.05	8,246.77
Happy Together 4	Entertainment	ON	5,403,939	3,920.39	55.46	13,281.91
Hello	Entertainment	ON	5,568,261	4,360.05	62.38	14,183.76
Young Fire	Entertainment	ON	6,845,178	4,415.16	53.25	14,406.57
My Little Old Boy	Entertainment	ON	6,957,347	5,213.81	65.9	14,846.45
Radio Star	Entertainment	ON	8,673,072	6,450.03	68.64	15,170.56
MEAN			2,228,886	1,454.45	47.62	3,971.56

Note: a unit of the inventory is impression (i.e., number of views).

values. However, the predictions were inaccurate with music (i.e., "The Show," "M COUNTDOWN") and entertainment news (i.e., "Cool Pick," "Amazing News").

B. COMPARISON WITH OTHER MODELS

To further validate the proposed method, we conducted an evaluation that compared the predicted results of XGBoost and Random Forest which are machine learning techniques. Since the machine learning algorithms are a type of supervised learning, it was necessary to change the data into a form of features and labels. Thus, we shifted each data set as a feature data and label. Known for their accurate forecasts, these techniques are ensemble models that predict time-series data [49]. We used the same period of data from the LSTM model to use with these machine learning models. Accordingly, we used 5-fold cross-validation to find an optimized hyper-parameter for each model. Selected main parameters for XGBoost were learning rate = 0.05, max depth = 5, and number of estimators = 300, whereas those for Random Forest were number of tress = 100, max depth of the tree = 100. The results of these comparisons are shown in Table 4. In the case of XGBoost, the range of result values for MAE were 345.95 $\sim$ 34,211.70; MAPE,34.78 $\sim$ 951.25; and RMSE, 557.77 $\sim$ 51,454.27 impressions. In the case of Random Forest, the range of result values for MAE were 532.45 $\sim$ 45,596.01; MAPE, 52.89 $\sim$ 1,687.39; and RMSE, 804.54 $\sim$ 73,315.64 impressions. Compared with other machine learning algorithms, the LSTM showed lower figures for MAE, MAPE, and RMSE. In other words, the LSTM performed best in predicting advertising inventory.

C. MONETARY VALUE COMPARISON

By using the actual advertising inventory amount, we compared the monetary values of the LSTM-based predictions and the current work-site predictions based on a statistical approach. There could be two cases in the sales of online advertising inventory: undersell (prediction < actual advertising inventory) and oversell (prediction > actual advertising inventory). Undersell is when additional sales cannot be made because the actual inventory is larger than the ad sales based on predicted inventory. Oversell is a case of non-compliance

TABLE 4. Analytical algorithm comparisons.

Channel Name	MAE			MAPE			RMSE		
	LSTM	XGBoost	Random Forest	LSTM	XGBoost	Random Forest	LSTM	XGBoost	Random Forest
Just happened	**43.33**	**1173.75**	**1858.80**	**30.35**	**907.07**	**1433.40**	**57.97**	**1588.73**	**3091.07**
A Collection of Songs on TV	**128.24**	**1813.49**	**2254.81**	**24.49**	**360.35**	**510.40**	**230.82**	**2628.38**	**3080.86**
eNEWS24	177.98	1777.39	2544.54	29.97	387.80	541.46	286.16	2671.55	4104.34
Dongchimi	261.42	365.76	532.45	48.61	94.94	153.10	385.22	578.53	1131.10
Manmulsang	140.64	1346.95	1962.78	36.04	540.18	813.00	395.48	1591.63	2401.67
NewsTrain	357.08	403.96	902.79	44.40	65.91	169.33	499.59	557.77	1174.85
Comedy Big League	275.58	4180.30	10050.81	34.61	634.41	1687.39	534.16	6624.25	16013.06
King of Mask Singer Special	**204.08**	**2900.94**	**3789.21**	**17.20**	**332.41**	**435.85**	**631.42**	**3263.63**	**4315.50**
Miss Trot	484.03	7535.99	8648.86	41.17	752.20	941.50	649.58	11634.95	14354.69
Yard in the Morning	334.58	453.59	559.12	43.13	70.95	112.31	654.71	744.07	804.54
TalkTalk	**323.35**	**1484.91**	**1917.16**	**20.54**	**151.89**	**189.91**	**678.21**	**1998.98**	**2300.15**
Ksintong	244.85	345.98	619.31	67.45	184.58	456.32	915.23	992.68	1282.20
Body God	583.28	1151.47	1385.84	52.03	120.85	176.70	1017.37	2175.53	2048.44
Morning wide	525.90	1266.09	2391.23	50.32	268.42	504.54	1080.26	2021.20	4223.95
Good Morning	484.89	585.38	920.97	42.77	73.73	135.74	1374.9	1361.80	1590.59
Battle Trip	474.14	1504.91	2643.11	55.84	517.27	933.68	1552.97	2098.67	3508.80
Baseball plus	1070.44	1459.62	2139.04	63.07	100.93	199.22	1640.81	2030.66	2775.69
2TV Live	757.77	1100.64	1390.47	56.30	140.97	213.62	1683.16	1964.24	2097.94
Thumb King	543.39	1857.92	2244.06	49.16	335.90	425.58	1703.99	2829.30	2999.54
Natural Person	756.73	1285.66	1833.63	52.18	131.89	257.44	2012.33	2992.67	3429.80
Amazing News	764.77	856.48	1122.27	79.28	123.69	205.12	2132.69	2247.44	2417.29
TV Zoo	822.81	3263.16	8580.03	46.51	516.33	1314.76	2229.6	4254.07	9511.27
Unanswered Questions	**1094.21**	**1657.51**	**2280.25**	**19.91**	**34.78**	**52.89**	**2301.62**	**2876.52**	**3773.41**
The Law of the Jungle	1186.59	3621.51	4730.46	35.72	182.14	246.39	2752.54	5897.57	6979.41
Sketchbook	1220.29	2810.49	4936.58	39.03	123.90	246.39	2840.96	5764.09	7784.21
The Show	1252.21	1664.54	1953.71	71.19	233.66	283.40	2914.86	3705.59	4152.13
Cool Pick	2113.88	4161.76	6104.33	71.93	335.61	557.59	4035.22	5329.74	7291.28
Music Core	2203.91	4149.03	4976.48	35.69	116.31	151.21	6995.61	7511.76	9550.40
Running Man	3638.07	4492.44	11505.47	36.05	60.50	160.83	8246.77	8256.29	21746.22
King of Mask Singer	3118.56	16319.18	19041.53	38.48	420.46	474.11	8610.95	24732.04	28525.20
M COUNTDOWN	2413.59	12237.46	15782.36	75.23	725.70	983.18	10041.59	24912.80	30689.30
Happy Together 4	3920.39	14416.83	14665.89	55.46	453.05	572.69	13281.91	28199.20	27370.36
Hello	4360.05	10672.54	11369.62	62.38	564.57	634.68	14183.76	19112.70	20546.92
Young Fire	4415.16	5579.98	5851.71	53.25	147.08	194.92	14406.57	14527.97	14912.25
My Little Old Boy	5213.81	34211.70	45596.01	65.90	951.25	1226.12	14846.45	51454.27	73315.64
Radio Star	6450.03	15454.64	16014.27	68.64	400.06	307.73	15170.56	23721.90	36883.29
MEAN	1454.45	4710.11	6252.78	47.62	321.16	497.29	3971.56	7912.59	10616.04

Note: bold indicates the best 5MAPE results among the channels.

with an advertiser because the actual inventory is smaller than the ad sales based on the predicted inventory.

In case of undersell (i.e., the predicted amount is smaller than the actual inventory), S-service may lose the opportunity of selling more online advertising inventory space. Thus, opportunity cost is incurred in the undersell case. In case of oversell (i.e., the predicted amount is larger than the actual inventory), S-service must compensate the advertiser with a penalty of twice the original amount for unexposed advertisements. Thus, penalty cost is incurred in the oversell case.

Table 5 summarizes the actual inventory, the LSTM based prediction, and the work-site based prediction for each channel. We then calculated the sales amount based on the online advertising inventory with the consideration of average CPM price (US$15). We also calculated the opportunity cost and penalty cost for each channel.

We first estimated and compared opportunity and penalty costs between the LSTM approach and the work-site approach in Table 5. As for penalty costs ((prediction inventory – actual inventory) $*$ CPM $*$ 2), they were incurred only by 2 channels ($6,527.40) out of 36 channels using the LSTM approach. In the case of the work-site approach, penalty costs were incurred by 21 channels ($206,546.94).

As for opportunity costs ((actual inventory -prediction inventory) $*$ CPM), they were incurred by 34 channels ($161,849.31) using the LSTM approach. In the case of the work-site approach, opportunity costs are incurred by 15 channels ($280,122,15). We could then calculate total cost based on the combination of opportunity cost and penalty cost. The total cost for the LSTM approach was $168,376.71 while that for the work-site approach was $486,669.09.

We then estimated Total Sales and Expected Value for the LSTM approach and work-site approach respectively. The total sales acquired through the LSTM prediction for 36 channels was $1,045,013.07(Prediction inventory $*$ CPM), the total opportunity cost $161,849.31, and the total penalty cost $6,527.40. As a result, the expected value that can be obtained from the LSTM model was $876,636.36(Total Sales-Total Cost). Whereas the total sales acquired through the work-site prediction was $1,026,750.00, the opportunity cost was $280,122.15, and the penalty cost was $206,546.94. Therefore, the expected value that can be obtained from the work-site was $540,080.91. The difference between the expected values of the LSTM approach and the work-site was $336,555.45 regarding the 36 channels for a duration of one month. Which means, the proposed LSM-based prediction method was more effective in generating revenue and increasing profit compared to the current work-site approach.

VI. DISCUSSION AND IMPLICATIONS

A. DISCUSSION OF FINDINGS

This study was about the prediction of advertising inventory for TV program-based online video channels. We used LSTM as a deep learning technique to predict advertising inventory for online video channels. In particular, we used the LSTM to predict online video advertising inventory based on real

TABLE 5. Comparison of monthly predictions (US$15 for CPM).

Channel Name	Actual Inventory	LSTM Prediction	LSTM Opportunity cost	LSTM Penalty cost	Work-site Prediction	Work-site Opportunity cost	Work-site Penalty cost
Just happened	108,195	98,249	$149.19	$0.00	150,000	$0.00	$1,254.15
A Collection of Songs on TV	**419,689**	**406,105**	$203.76	$0.00	**500,000**	**$0.00**	$2,409.33
eNEWS24	408,620	378,842	$446.67	$0.00	500,000	$0.00	$2,741.40
Dongchimi	443,455	387,304	$842.27	$0.00	500,000	$0.00	$1,696.35
Manmulsang	287,150	255,732	$471.27	$0.00	500,000	$0.00	$6,385.50
NewsTrain	**660,102**	**631,327**	$431.63	**$0.00**	**1,000,000**	$0.00	$10,196.94
Comedy Big League	**594,164**	**569,955**	$363.14	**$0.00**	**700,000**	$0.00	$3,175.08
King of Mask Singer Special	724,408	677,575	$702.50	$0.00	400,000	$4,866.12	$0.00
Miss Trot	1,010,026	806,884	$3,047.13	$0.00	1,500,000	$0.00	$14,699.22
Yard in the Morning	612,917	528,867	$1,260.75	$0.00	1,000,000	$0.00	$11,612.49
TalkTalk	**1,083,767**	**1,042,546**	$618.32	**$0.00**	**500,000**	$8,756.51	$0.00
Ksintong	240,437	141,652	$1,481.78	$0.00	300,000	$0.00	$1,786.89
Body God	933,470	888,001	$682.04	$0.00	1,500,000	$0.00	$16,995.90
Morning wide	860,054	757,890	$1,532.46	$0.00	1,000,000	$0.00	$4,198.38
Good Morning	681,913	522,659	$2,388.81	$0.00	1,000,000	$0.00	$9,542.61
Battle Trip	529,518	371,238	$2,374.20	$0.00	800,000	$0.00	$8,114.46
Baseball plus	1,540,826	1,338,040	$3,041.79	$0.00	2,000,000	$0.00	$13,775.22
2TV Live	1,002,691	803,744	$2,984.21	$0.00	1,500,000	$0.00	$14,919.27
Thumb King	707,392	509,998	$2,960.91	$0.00	1,000,000	$0.00	$8,778.24
Natural Person	1,017,741	785,391	$3,485.25	$0.00	400,000	$9,266.12	$0.00
Amazing News	870,076	682,998	$2,806.17	$0.00	1,500,000	$0.00	$18,897.72
TV Zoo	1,089,067	859,363	$3,445.56	$0.00	300,000	$11,836.01	$0.00
Unanswered Questions	3,543,785	3,358,162	$2,784.35	$0.00	2,000,000	$23,156.78	$0.00
The Law of the Jungle	2,199,586	1,958,071	$3,622.73	$0.00	2,500,000	$0.00	$9,012.42
Sketchbook	2,288,923	2,175,121	$1,707.03	$0.00	1,500,000	$11,833.85	$0.00
The Show	1,348,297	1,004,668	$5,154.44	$0.00	900,000	$6,724.46	$0.00
Cool Pick	2,440,329	1,887,161	$8,297.52	$0.00	1,000,000	$21,604.94	$0.00
Music Core	4,008,277	3,641,621	$5,499.84	$0.00	2,000,000	$30,124.16	$0.00
Running Man	6,682,419	6,757,542	$0.00	$2,253.69	3,000,000	$55,236.29	$0.00
King of Mask Singer	**4,749,379**	4,520,608	$3,431.57	**$0.00**	**5,000,000**	$0.00	$7,518.63
M COUNTDOWN	3,705,442	3,847,899	$0.00	$4,273.71	5,000,000	$0.00	$38,836.74
Happy Together 4	5,403,939	3,712,520	$25,371.29	$0.00	5,000,000	$6,059.09	$0.00
Hello	5,568,261	4,634,139	$14,011.83	$0.00	5,000,000	$8,523.92	$0.00
Young Fire	6,845,178	5,390,835	$21,815.15	$0.00	5,000,000	$27,677.67	$0.00
My Little Old Boy	6,957,347	5,931,757	$15,383.85	$0.00	6,000,000	$14,360.21	$0.00
Radio Star	8,673,072	7,403,074	$19,049.97	$0.00	6,000,000	$40,096.08	$0.00
Total Sales (Prediction * CPM)		$1,045,013.07			$1,026,750		
Total Cost			$161,849.31	$6,527.40 ($168,376.71)		$280,122.15	$206,546.94 ($486,669.09)

Note: bold indicates the best 5 results (The proportion of the difference compared to the actual Inventory) among the channels.

user data, compared our results with other machine learning methods (i.e., XGBoost and Random Forest), and confirmed the superior performance of LSTM by comparing it with values predicted by the actual work-site provider of real online video and advertising services. Overall, the results of the advertising inventory predictions gained by using the LSTM of deep-learning algorithms were better than others. Based on the numbers we used for comparisons, this additional value could reach about $336,000 a month, illustrating the potential practical value of a more accurate predictive model.

Based on qualitative interpretation of the proposed method (see 5.4), we could discern additional insights that were not available in the test results of the model. For the online video channels currently broadcasting on TV, the advertising inventory was shown to be high during the 24 hours after broadcasts. Meanwhile, with online channels provided in a closed program on TV or an online-exclusive channel, advertising inventories showed consistent patterns, increasing at certain times and then reverting to their original patterns. Interpretation of these patterns is, in the case of the channels currently broadcasting on TV, that viewers who watched a specific program on TV might search and watch relevant programs on its online channel. In other words, they additionally search and watch the relevant online channel at the time the preferred program was also being broadcasted on TV. On the other hand, with closed channels on TV or online-exclusive channels, because they are not currently broadcasting on TV, there is no relation to a TV broadcast time, which leads to an interpretation that the online channel is watched a lot during a specific time period such as a weekend.

However, in the case of music programs (i.e., ''The Show,'' ''M COUNTDOWN'') and entertainment news (i.e., ''Cool Pick,'' ''Amazing News''), the accuracy of the predicted advertising inventory was unsatisfactory. This could be interpreted that in the case of such music and entertainment news programs, the views of online channel for the program increase more when a popular guest shows up. Another possible interpretation is that the viewers for these channels are more sensitive than others to broadcasting schedules and program cancellations. Based on the results of our study, we can suggest guidelines and strategies for the execution of online channel-based video advertising.

Moreover, as a result of our study, we have added to the literature in the online advertising field by showing the efficacy of applying deep learning techniques to the prediction of online advertising inventory.

B. LIMITATIONS AND FUTURE RESEARCH

The limitations of this study and future research directions are as follows. First, this study predicted the inventory per time period in a program unit. In future studies, this utilization can be enhanced by predicting in units of minutes of the unit. Second, because we limited the scope to online video channels related to TV programs, future research can extend the scope to multichannel networks (MCNs) [50]. In other words, more and more channels are gaining popularity as various online content is created; similarly, TV programs based on online content distributed through online platforms such as YouTube are proliferating. In this study, the location where a program was aired had an impact on the prediction results. But expanding research to MCNs could engender characteristics unlike those in this study and thus require differentiated advertising execution strategies for each online video channel. Third, the predictive power of LSTM with deep learning techniques has been improved through the development of ensemble or hybrid models in combination with other algorithms [40] and has the potential to further improve predictions of advertising inventory in future studies. Especially, a deep transformer model was developed to more effectively predict time series data [51]. This method operates by leveraging the self-attention process to learn a complex pattern of time series data. Further studies should consider this method to predict online video advertising inventory.

C. IMPLICATIONS FOR RESEARCH AND PRACTICE

As watching online videos has recently increased, the interest and investment in online advertising are also on the rise. This is a phenomenon that is expanding from traditional advertising in TV, radio, and newspaper to online advertising. Followingly, the prediction of online advertising inventory is also increasingly significant. In other words, the accurate prediction of vendable advertising space can lead to more profits. Thus, this study, predicted online advertising inventory using deep learning based on users' log data and verified it. This study has several implications for research and practice.

First, we developed a method to use deep learning techniques to predict online video advertising inventory. Our usage of these techniques reflects the recent increase in interest in the use of big data, machine learning, and artificial intelligence (AI) in various fields, especially in online advertising and marketing [52], [53]. The analytical methods that learn from past data are relevant for marketing because they facilitate intelligent business practice [38]. Programmatic advertising based on data analysis has been in the spotlight of online advertising, which is used as a core technology for inventory prediction [54]. Inventory prediction is considered an important issue in the advertising market and related fields. The more accurate the delivery of inventory predictions, the more clearly advertisers can present their advertising strategies that ultimately result in the maximization of media companies' advertising revenue. According to an interview with the manager of a service provider, most service providers use simple statistical applications with acknowledged insufficient accuracy. They continue to use these poorly performing applications despite their belief that accurate prediction of advertising inventory is the key to increased profits. Besides, even though the prediction of advertising inventory in the advertising market is important, no study of the subject has been made so far. There are various types of studies about prediction in other fields, and some recent studies have applied machine learning or deep learning techniques to make predictions in fields such as daily long-term traffic flow and film performances and sales [32], [33], [35]. Therefore, the significance of this study is the use of deep learning techniques in the development of a highly accurate model to predict advertising inventory as an essential part of the trend toward programmatic online advertising based on detailed analyses of consumer data. Therefore, the deep learning methods presented in this study hold out the promise of superior alternatives with greatly increased predictive power.

Second, we developed an advertising predictive model based on actual inventory data of 36 channels that could be applied to the actual online advertising market. Additional profits are expected as this predictive model is put into use. Most companies, which are service providers, predict online video advertising inventory through simple statistical applications with a low prediction rate, so they sell the inventory by lowering the results than the predicted ones. However, when the LSTM suggested in this research is used to predict online video advertising inventory, the prediction performance is high, and profits through sales are expected to increase because the advertising inventory does not have to be sold at lower quantities than the actual prediction results. Using the method developed in this study to predict advertising inventory could generate additional profit. Additionally, service providers that already predict online video advertising inventory using the hybrid model can comprehend the differences and characteristics of prediction rate according to genres and types of programs through the results of this study and can consider them in selling the advertising inventory.

Third, through the results of this study, we can suggest to practitioners of online advertising services some detailed strategies for the execution of online video advertising. For the prediction of the advertising inventory of online channels based on broadcasting programs, practitioners need reliable predictions for the broadcast time of each program and the characteristics of each genre. Through this study, the online video of the TV program being aired showed an increase in inventory over the 24 hours after a program was aired. On the other hand, in the case of an online video of a closed program on TV or an online-exclusive channel, the inventory was found to be increased slightly at the time of uploading new content or on weekends. If based on the results of this study, the advertisement is provided to an online channel that is aired on TV, it is desirable to execute an advertisement at the time when the relevant TV program is aired. On the other hand, if an advertisement is provided to a closed program on TV or an online-exclusive channel, it is better to execute an advertisement when new content is uploaded or on weekends when people watch online videos the most. Also, concerning the genre of channels and especially applicable to music and entertainment news programs, inventory predictions should be able to encompass the potential impact of cancellations and the presence or absence of favored performers and celebrities. When "music" and "entertainment news" genres are involved, the prediction of advertising inventory becomes more difficult because viewer ratings are highly variable in response to which specific events, celebrities, or performers are featured. Therefore, predictions of the advertising inventories of these genres should be linked as closely as possible to specific events, appearances, or performers.

Moreover, the model suggested in this study can be used in media, content, and advertising companies in a variety of ways. Media companies, which are service providers, can predict and sell optimal online video advertising inventory using this model. They can also establish differentiated advertising inventory sales strategies according to program genres and types based on the results of this study. Contents companies, which are broadcasting companies, can use this model to plan distributed channels (i.e., broadcasting programs). Based on the results, they can engage in sales differently depending on genres and types of broadcasting programs. Also, various overseas channel contents are traded and distributed due to the recent increase of online video views across the world, so the suggested model in this study can also be used for overseas content. Advertising companies can utilize the results not only to maximize the reach but also to suggest appropriate channels (i.e., broadcasting program) to certain brands companies that intend to advertise their products.

Fourth, we used both internal and external feasibility studies to increase the validity of online advertising inventory predictions. To examine internal validity, we compared the predicted values of our developed LSTM algorithm-based model and those of two machine learning models (i.e., XGBoost and Random Forest). For the external feasibility review, we compared the predicted values of actual companies that provide online video and advertising services. In these comparisons, our LSTM algorithm-based model with a deep learning method showed the best predictive power.

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