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ORIGINAL ARTICLE

Detectability of Sports Betting Anomalies Using Deep Learning-based ResNet: Utilization of K-League Data in South Korea

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ABSTRACT

Background. Sports match-fixing refers to the act of pre-determining the results of a game. Match-fixing fundamentally undermines competition in sports, and it harms society as a whole. Match-fixing has large as it is conducted as a secret transaction. Consequently, finding evidence regarding this illegal activity or detecting it is difficult. Therefore, a system should be built to detect match-fixing to prevent it. **Objectives.** This study aims to detect betting anomalies in sports events through dividend graphs. **Methods.** We collected the odds data for the K-League from 2010 to 2020 and converted the data into graph images to generate 3101 graph images. The collected data was analyzed using ResNet to classify them into normal games (2,464 games) and abnormal games (637 games) based on an image classification method. The ResNet model was trained for 100 epochs, and as a result, values below 0.05 were derived as the loss values of the training and test data, respectively. **Results.** After performing the validation with the test data of 50 normal and 27 abnormal games, it was found that the accuracy in deriving normal games was 90%. Furthermore, match-fixing games were derived with an accuracy of 74.1%. Therefore, the model was accurate for 65 out of 77 games, showing that the model's accuracy was 84.44%. **Conclusion.** The results demonstrate the model's value as a method for detecting sports match-fixing. Additionally, it can aid in eradicating sports match-fixing by providing the basic data for undertaking detailed match-fixing investigations.

KEYWORDS: ***Match-Fixing, Deep Learning, Artificial Intelligence, Football.***

INTRODUCTION

Anomaly detection refers to the process of finding unexpected patterns in data. Anomaly detection is used in various fields, including finance, cybersecurity, behavioral patterns, game development, and industrial systems (1-3). For example, credit card usage data are used in the financial sector to detect cases of illegal or misuse. Similarly, it is used in the gaming sector to detect fraudulent or unethical activities. Thus, anomaly detection is used to detect malicious actions or abnormal situations. Accordingly, efforts have been made to build anomaly detection systems to prevent damage in various fields.

Consistent efforts have been made to build anomaly detection systems in sports (4). The need for these systems is expedited by the International Olympic Committee's (IOC) declaration that sports match-fixing is a global challenge for sports in the 21st century. It has led to adopting measures, such as monitoring systems, to prevent match-fixing (5).

Sports match-fixing refers to the act of pre-determining the results of a game (6). Match-fixing fundamentally undermines competition in sports and harms society as a whole (7). For example, continuous occurrences of match-fixing can lead to a decline in the interest in and

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popularity of a sport. Furthermore, the decline in trust between players, teams, and fans can cause damage in various sectors, such as sports, society, and industries (4).

Despite recognizing its adverse effects, it is difficult to cull match-fixing. Thus, match-fixing has large as it is conducted as a secret transaction. Consequently, finding evidence regarding this illegal activity or detecting it is difficult (8). Therefore, a system should be built to detect match-fixing to prevent it.

Recent advancements in sports science and statistical analysis techniques have led to studies seeking match-fixing evidence from ordinary data (9, 10). A previous study explained that "fixed matches" data showed abnormal patterns or signals, unlike ordinary data (10). Hence, continuous efforts have been made to solve the sports match-fixing problem using traditional statistical methods. In particular, Sportradar uses outliers in odds to detect games suspected of being "fixed." Besides, studies have been conducted to detect match-fixing using odds (10, 11). These methods of detecting anomalies in the odds can be seen as effective for detecting match-fixing since the Court of Arbitration for Sport (CAS) accepts it as major evidence in sports match-fixing cases (12).

The use of odds is an effective method to detect match-fixing, as the main goal of sports match-fixing is to gain high dividends through sports betting (13). Accordingly, previous research focused on the odds among numerous data of sports events. Furthermore, odds can be used to check the strength of both teams as their values change continuously over time. That is, the odds are numerical values that can be used to predict the outcome of a match. The ease of using odds data as a single numerical value to detect anomalies has led to their extensive use in many studies.

Previous studies had several limitations despite efforts to detect match-fixing using statistical methods. Finding anomalies through odds analysis and making decisions about the anomalies are tasks that require significant amounts of workforce and labor due to the existence of many sports and leagues that belong to each sport. Therefore, previous studies used data on a particular sport to detect anomalies in past games. Consequently, these methodologies can only be used to assess match-fixing in previous games. Developing a new methodology to detect anomalies in future games is necessary.

Artificial intelligence (AI) has recently been used in various fields owing to the advancement of deep learning. Specifically, deep learning algorithms have been used to detect the fraudulent use of credit cards (14-16), insurance fraud detection (17), and cell phone fraud detection (18). Therefore, the effectiveness of AI in detection activities based on the advancement of deep learning technology has been proven.

In particular, the convolutional neural network (CNN) demonstrated its effectiveness in the ImageNet Challenge, an image classification competition (19). CNN is representative of a deep neural network. It is mainly used for image classification, face recognition, and image analysis. It was developed through LeNet, proposed by Frenchman Yann Lecun, in 1998 (20). CNN learns images by grasping patterns through extracted data features, and its performance reports are generally excellent (21). CNN is also used as a basic algorithm in Google's AlphaGo (22), and it is positioned as a deep learning algorithm that can replace the role of humans in the field of images. Therefore, CNN can detect anomalies in sports match-fixing.

This study aims to implement a deep learning algorithm that can detect anomalies by converting the odds data of sports games into a graph image. This study is significant because it proposes a new method for detecting sports match-fixing.

MATERIALS AND METHODS

This study uses the dividend graph to detect betting anomalies in sports events.

The program learns to classify normal and abnormal games by studying dividend graphs of sports, then uses the image classification method to classify future games. Abnormal games are defined in this study as games in which anomalies are detected. In deep learning, ResNet, based on CNN, the foundation of image classification, is used to analyze images. The ResNet used here shows satisfactory performance that can improve accuracy in deep learning.

Convolutional Neural Networks (CNN). CNN is a method for analyzing two-dimensional (2D) data. It is a method that flattens existing data and learns the features of 2D images to understand the spatial and local information lost in learning a single line of data. Since CNN is trained by receiving an image as a raw input, it hierarchically derives features of each training image while maintaining the spatial/local information. Therefore, it is a method that finds features by learning patterns in an image. When a new image is an input, it finds a group of the most similar images based on the existing features. CNN is divided into the feature extraction stage and the classification stage. The feature extraction stage consists of a convolution layer and a pooling layer. In the convolution layer, various features of one input image are derived according to the number of specified channels. The size of the channels with various features for an image can be decreased to emphasize specific features and reduce the computational amount of training in the pooling layer. In the classification stage, based on each image feature after undergoing the pooling layer, the activation function of the fully connected layer is used to determine the group closest to the input image.

ResNet. The ResNet model reduces the depth of the learning layers compared to the CNN model, which is a traditional image analysis model. It improves performance and accuracy through residual learning. In a typical CNN, many layers are stacked to increase learning accuracy. However, deep layers can reduce the learning model's accuracy. As such, CNN-based learning models have difficulties in learning to optimize for many parameters. Therefore, when ResNet derives a value from the weight layer, through the activation function in the convolution operation, it fetches the previously learned information as is, and learns F(x), the residual information, as shown in Figure 1. On examining the equation, we made the following observation. When an input value x is entered, it is multiplied by the first weight value, and the activation function and second weight value are multiplied. Here, the x identity, the x value, is multiplied additionally. Therefore, as a result, is derived by continuously repeating this process, the multiple convolutional layers — F(x,{wi}), and the Shortcut Connection Wsx, which brings the current input value as is, are added to the result value, to derive y.

$$y = F(x, \{W_i\}) + W_s x$$

Thus, information is added to the result derived from the weight layer. Since the computational complexity can be reduced, a model with faster training and better performance can be derived.

Data Analysis. The data collected in this study are the dividend data of the K-League (including the K-League 2 and Cup Competition) from 2010 to 2020 collected through 12 sports betting sites (188bet, Interwetten, vcbet, 12bet, willhill, Macauslot, sbobet, wewbet, mansion88, easybet, Bet365, and Crown). First, the collected data were converted into images in the form of graphs, and finally, 3,101 graph images were created for the win, draw, and loss odds (1*2 odds).

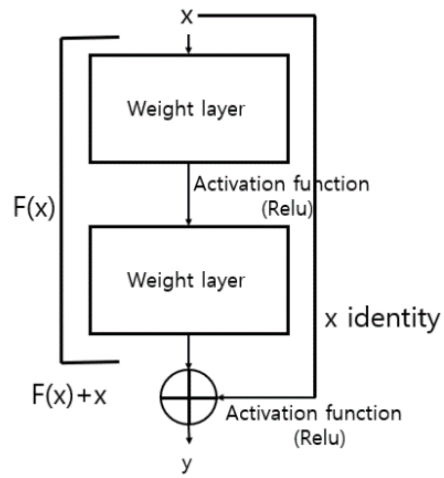

Figure 1. ResNet Process

In the graph image, the X-axis represents time, and the Y-axis shows three odds (blue for win, red for drawing, and green for loss) based on the home game of each match. The data were merged primarily according to the time order without distinguishing the betting sites. Here, the dividend graph was created by displaying a line for the points of all values of the dividends and a thick line—which can represent the overall trend for the dividend point at each time point—for the dividends of win, draw, and loss, respectively (Figure 2).

This study requires the learning algorithm's normal and abnormal game data. If only the data determined as match-fixing are used for training, the data will be small, and the training data may be biased toward normal games. Therefore, when the program analyzed 3,101 collected images (excluding the 77-test data), it checked whether the game showed a similar pattern to games determined to be "fixed" based on previous studies. If the patterns were similar, they were determined to be a game suspected of match-fixing. Accordingly, it was classified as data from an abnormal game and used in training. Two sports game analysis experts, two Ph.D. degree holders in Measurement and Evaluation in Physical Education, and one Ph.D. degree holder in Industrial System Engineering participated in the data classification to ensure the validity of the data.

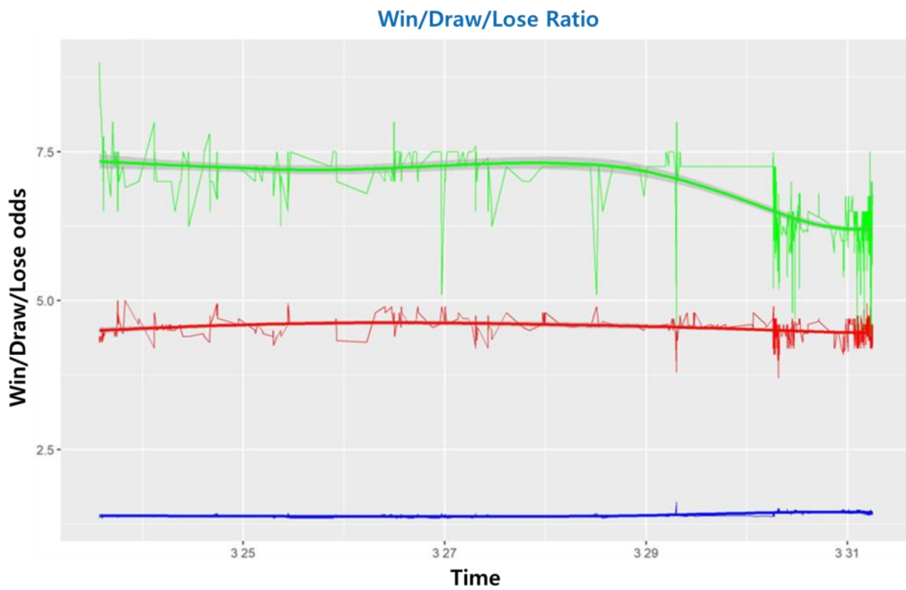

Figure 2. Graph of win, draw, and loss odds

For the classification of abnormal games, we chose graphs that showed four odds trends, as shown in Figure 3. In Figure 3, data were generated for abnormal games through the following four cases of dividend movements: (1) a graph in which the odds change rapidly, or the result is reversed suddenly for the game; (2) a graph in which the odds proceed in similar flows, and then a difference appears suddenly between two odds; (3) a graph in which the odds of the game outcomes change consistently with each other and then rapidly show differences; (4) the dividend graph moves irregularly for a certain game outcome. The total amount of data collected for abnormal data was 637. In short, the classification performed based on the training with 2,464 normal games and 637 abnormal games was applied to our model.

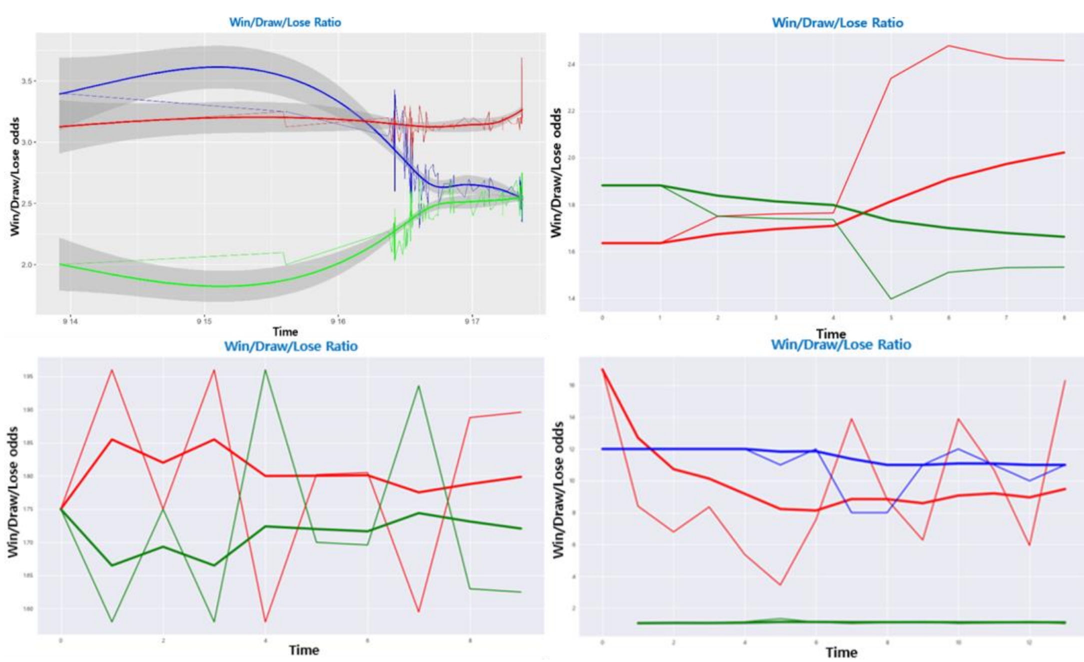

Figure 3. Graphs for abnormal games. Case 1 (upper left): where odds change rapidly, or the result is reversed suddenly for the game; Case 2 (upper right): where the odds proceed in similar flows, and then a difference appears suddenly between two odds; Case 3: where the odds of the game outcomes change consistently with each other and then rapidly show differences; Case 4: where the dividend graph moves irregularly for a certain game outcome.

The ResNet model was trained using the training data to find features, and the features were used to train the Deep Neural Network (DNN) model specializing in simple classification to derive normal and abnormal games. Figure 4 shows the model's overall process. As shown in Figure 4, we collected odds data from sports games. The odds data were provided by the iSports API (https://www.isportsapi.com/). We refined the odds data in 10-minute intervals from when the game odds were assigned. The refined odds data were then converted into a graph, and the games were classified into normal and abnormal games, respectively, based on the patterns of abnormal games defined in Figure 3. As a result, 2,464 graph data for normal games and 637 graph data for abnormal games were created. Using the created data, the features of normal and abnormal games were learned through ResNet. After flattening the features of the images learned through ResNet, normal and abnormal games were derived through the classification model.

RESULTS

This study created a model that identifies normal and abnormal games by learning graph images of sports odds data. The model was trained using ResNet, achieving high accuracy even when the model's learning depth increases in image analysis. The ResNet model was trained for 400 epochs, resulting in values below 0.05 for the training and test data loss values. After training the model, we used the odds data of the following games as test data: 50 normal games and 27 abnormal games determined to be "fixed." The number of cases of match-fixing was small. Therefore, the number of abnormal games is significantly smaller than that of normal games in the test data. To minimize the bias in the test data, we used the data of win, draw, and loss odds (1*2 odds) and over/under odds as test data. Figure 5 shows odds graphs based on the match-fixing game dataset.

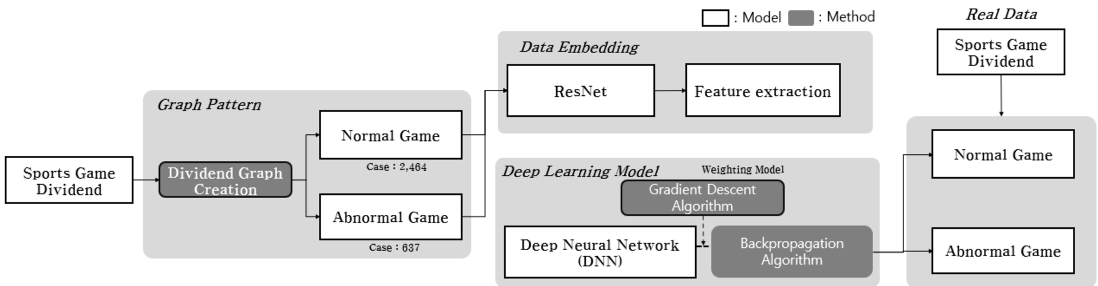

Figure 4. Match-fixing classification model's process

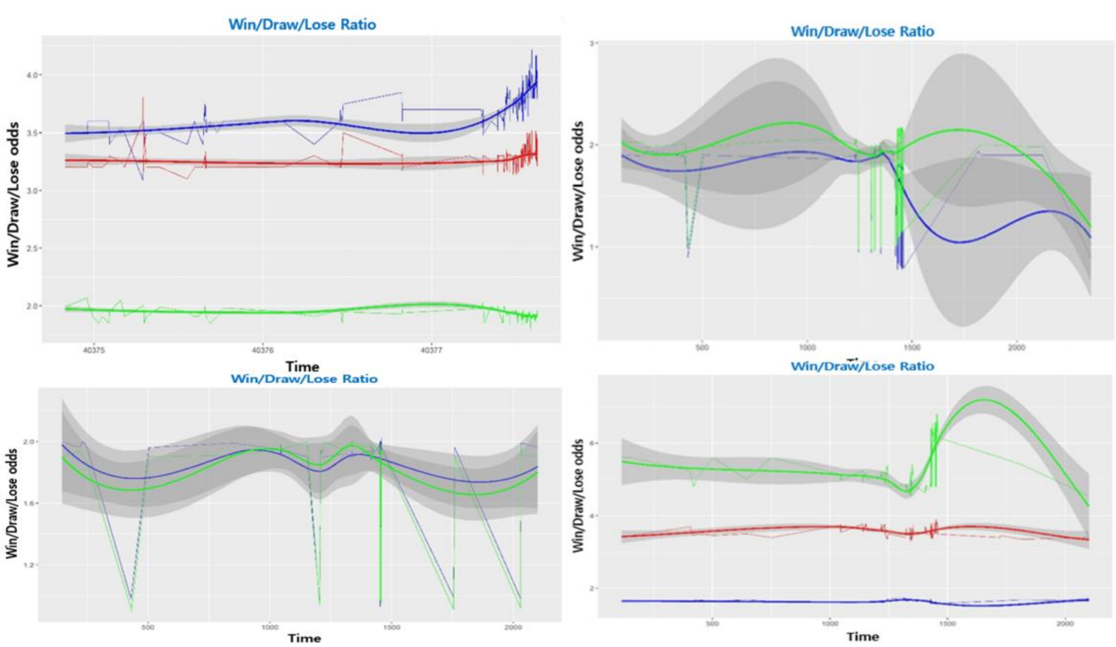

Figure 5. Dividend graph structures of the test data.

We validated the match-fixing classification model using a total of 77 test data. According to the result, the precision was 0.753, and the recall was 0.51. In the performance evaluation of the model, the Area Under the ROC Curve (AUC) was 0.861. When the confusion matrix was examined, 83% accuracy was derived for the test data, as shown in Table 1.

Table 1. Confusion Matrix

		Predicted	
		Normal games	Match-fixing games
Actual	Normal games	45	5
	Match-fixing games	7	20

Figure 6 shows that the training and test data loss values were derived based on this. Table 1 shows a confusion matrix for the result of inputting the test images. Table 1 shows a 90% probability of accurately deriving normal games among 50 normal games and 27 match-fixing games. Furthermore, match-fixing games were detected with 74.1% accuracy. Thus, when the total accuracy is examined, 65 out of the 77 games were determined accurately, showing that the model has 84.44% accuracy.

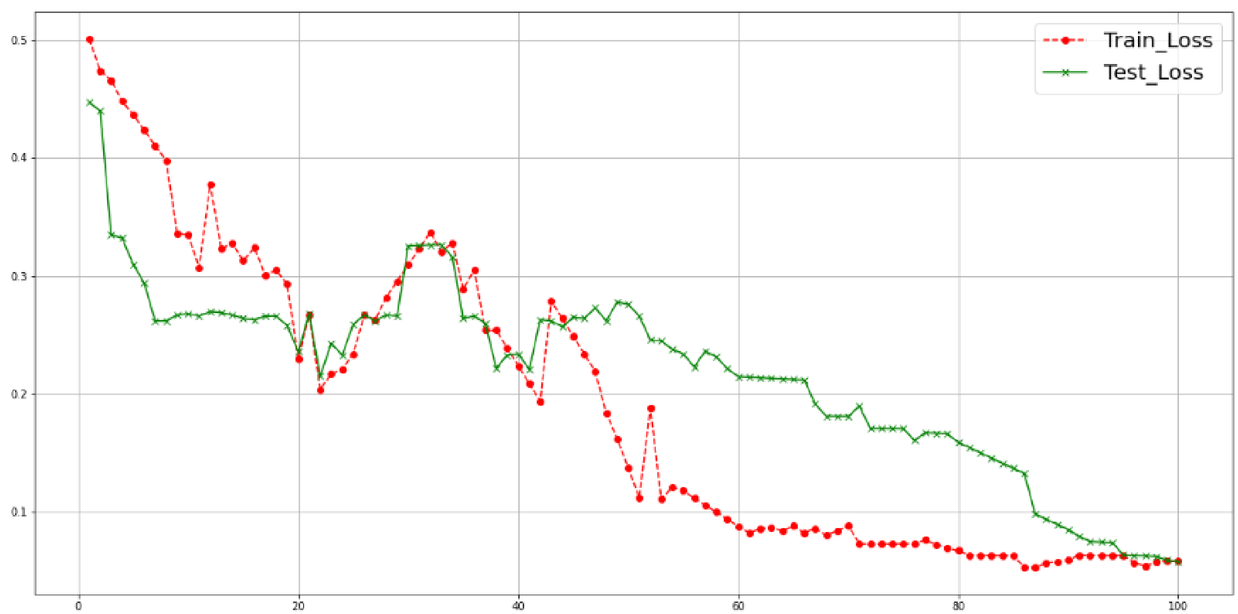

Figure 6. ResNet Loss (Training/Test).

DISCUSSION

Match-fixing is an ongoing issue in sports. Recently, the sports industry has been hit by a major financial blow due to the restrictions, such as the suspension of professional sports leagues and restrictions on the presence of spectators, due to the COVID-19 pandemic. Consequently, sports clubs, players, coaches, and referees have become vulnerable to match-fixing (23). Several methods have been proposed to detect match-fixing using sports odds to solve the match-fixing problem. However, they mainly analyze the statistics of odds and probabilities to detect match-fixing. Hatfield (23) created prediction models through statistical analysis methods using the odds. When the actual data exceeded the threshold of the prediction model, they were considered outliers and determined as games suspected of match-fixing. These methods can help detect match-fixing. However, since they find outliers based on simple numbers and probabilities, there is the possibility of minor errors, which are not shown statistically. Thus, there is a limit to considering countless detailed variables, such as special external factors, that can change the game's outcome. Therefore, we deliberately pre-determined the match's outcome for each team's internal personnel and judged the fixed match using this as a bet. Therefore, this study converted the flow of odds into an image for the continuous monitoring and blocking of match-fixing and proposed a novel model based on deep learning to detect match-fixing.

CONCLUSION

The first objective of this study was to implement a deep learning-based algorithm that can detect anomalies. It is important to secure high-quality training data when implementing the algorithm. However, in the case of abnormal games, they could not be used as training data as only a small number of games were judged as match-fixing. Therefore, we classified normal games (2,464 games) and abnormal games (637 games) in this study by comparing them to the patterns of the odds data of match-fixing games in the collected 3,101 data through the expert group meeting and using them as training data. In a previous study that detected match-fixing statistically (23), the limitation was that a small number of games were determined to be match-fixing. Therefore, we classified the training data through the method mentioned previously to solve this problem.

Second, through the above process, we constructed an anomaly detection model using deep learning-based ResNet in this study. The model was validated using 50 normal and 27 abnormal games in which illegal match-fixing occurred. Examining the model's accuracy, we found that the accuracy was 90% for normal games and 74.1% for abnormal games. In sum, the overall accuracy of the model was 84.44%. Since the actual number of games in which match-fixing had taken place was not used in the training data, they could be used as test data. It means that the performance of the anomaly detection algorithm developed in this study could be diagnosed more accurately. Through the model results, the team's insiders can detect an abnormal match by exposing a match-fixing pattern that intentionally changes the match result before the start of the game to obtain the benefit of sports betting.

Although there were many cases and data for normal games, there was a limitation in finding various cases for abnormal games in the results of constructing the model in this study. This phenomenon is because although many match-fixing events occur in sports matches, few matches are reported and proven to indulge in match-fixing through police investigations. Moreover, while there have been cases of match-fixing, these are suspicious cases. These matches were not proven to be fixed, so it was impossible to use them as data. It led to the class imbalance problem in constructing the learning model. Therefore, in future studies, we will additionally investigate cases of various sports to improve the overall accuracy and perform analysis by increasing the number of abnormal games by additionally collecting cases suspected of illegal match-fixing games based on expert opinions. We expect that the accuracy of match-fixing classification can be enhanced if data are collected continuously and the additional patterns of normal and abnormal game outcomes are classified. In recent years, betting items for various specific situations (Goal scorers, Match Card, Scoring a Penalty), in addition to the simple win, draw, and loss odds, are increasing, and there is a high possibility that match-fixing will take place in these types of betting. Ötting, Langrock, and Deutscher (11) determined outliers in betting volumes using distinct types of odds data to detect match-fixing and showed that the match-fixing detection accuracy improved when odds and betting volumes were combined in the model. Therefore, the model's accuracy can be improved in future studies based on increasing the number of test data and improving the feasibility of validation by collecting data on various betting types and other variables besides bets on wins or losses.

Match-fixing games cannot be classified perfectly based on abnormal odds data alone (10). However, this analysis will aid in determining the differences between normal and abnormal games in advance, which can then be subjected to a more detailed match-fixing investigation process. Therefore, the result of this study is valuable as basic data for detecting match-fixing in sports and can be presented as a solution to eradicate sports match-fixing. In addition, match-fixing cases are gradually collected through this study's model. Sports players and sports-related personnel can improve their skills in a better environment through the collected data and higher accuracy for detecting match-fixing. An infrastructure can be built to prove this.

APPLICABLE REMARKS

- The result of this study is valuable as basic data for detecting match-fixing in sports.
- This study can be presented as a solution to eradicate sports match-fixing.

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AUTHORS' CONTRIBUTIONS

Study concept and design: Ji-Yong Lee, Changgyun Kim. Acquisition of data: Daegeon Kim. Analysis and interpretation of data: Changgyun Kim, Jae-Hyeon Park. Drafting the manuscript: Ji-Yong Lee, Changgyun Kim. Critical revision of the manuscript for important intellectual content: Jae-Hyeon Park. Statistical analysis: Changgyun Kim. Administrative, technical, and material support: Jae-Hyeon Park. Study supervision: Jae-Hyeon Park.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

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