

Detecting Sports Spoiler Images on YouTube

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Abstract. Spoilers of sports matches reduce the enjoyment of time-shifted viewing. On YouTube, users who like sports often inadvertently know the outcomes of matches by seeing thumbnails of recommended sports videos. Therefore, this paper focused on YouTube video thumbnails and verified the possibility of detecting images that contain spoiler information on YouTube. We constructed a dataset of sports spoiler images comprising 4,531 thumbnails from baseball, soccer, and basketball. In addition, we proposed three detection methods: the Image-Recognition method using optical character recognition (OCR), emotion assessment, and posture assessment; the Vision-Direct method using the OpenAI Vision API only; and the Vision-Text method that judges using the spoiler dictionary for an image’s description by the OpenAI Vision API. We evaluated the accuracy of these methods, and our results indicated that the Vision-Text method achieved an accuracy of 85% in detecting spoiler images. Furthermore, the evaluation results indicated that the Vision-Text method might be the most effective for detecting spoiler images in baseball and soccer. In contrast, the Vision-Direct method seems to be the most effective in basketball.

Keywords: Spoilers, Sports images, YouTube, ChatGPT.

1 Introduction

Watching sports matches is popular all over the world, and one of the reasons for this is that the unpredictability of the results evokes excitement [1]. For this reason, many people prefer to watch matches in real time, but time differences or personal reasons often make this impractical. In such cases, recording or rebroadcasting matches offer alternatives for enjoying the matches at one’s own convenience. However, when intending to watch a match later, people may inadvertently encounter information about the sports match through social networking services, video-sharing sites, and news sites before watching the match. This information about sports match outcomes is called a *spoiler*, and spoilers reduce tension and enjoyment when watching sports [2].

To prevent sports spoilers, Nakamura et al. [3] proposed a method for blocking spoilers on the web by ambiguating textual information about sports matches. Sasano et al. [4] detected tweets containing spoilers of baseball games using a personalized support vector machine. These studies focused on spoilers in text, but sports spoilers also exist in images. For instance, Fig. 1 is a soccer image without direct information about the winner or loser, but fans may predict the match outcome from the players’

facial expressions. Previous studies targeted textual spoilers and no methods for preventing spoilers through images have been proposed.

People can encounter spoiler images under various circumstances. For instance, while using social networking services to catch up with friends or searching for videos on video-sharing sites, people might inadvertently discover the results of sports matches through images posted on social networking services or by seeing thumbnails of recommended videos (see Fig. 2). In this study, we focus on spoilers given through thumbnails on YouTube because avoiding spoilers on YouTube is difficult due to its recommendation algorithm. For example, if a user often watches sports videos, YouTube is likely to recommend sports content even when watching different content types. Consequently, users may encounter sports spoilers through the thumbnails of these recommended videos. Therefore, preventing image-based spoilers on YouTube is important for those who wish to enjoy sports matches without spoilers.

This paper verified the possibility of detecting spoiler images to prevent spoilers through images. We constructed a dataset of sports spoiler images and analyzed their features. Furthermore, we proposed three methods for detecting spoiler images and evaluated the performance of our methods.

The contributions of this paper are as follows:

- (1) We categorized spoiler images into two types, direct and indirect spoilers, and defined spoiler images as images that enable the prediction of match outcomes based on preliminary investigation.
- (2) We constructed a dataset of sports spoiler images consisting of 4,531 thumbnails extracted from YouTube videos of baseball, soccer, and basketball and annotated by three collaborators.
- (3) We achieved 85% accuracy in detecting spoiler images by describing an image as a text and matching the words with our spoiler dictionary.

2 Related Work

2.1 Spoilers

Leavitt et al. [5] investigated the impact of spoilers on the enjoyment of novels and found that spoilers do not necessarily reduce enjoyment. In contrast, Rosenbaum et al. [6] discovered that people not accustomed to reading novels tend to find stories with spoilers more appealing, whereas avid readers prefer stories unspoiled. In addition, Levine et al. [7] showed that encountering spoilers before reading a novel can diminish its attractiveness. Maki et al. [8] investigated the effects of spoilers depending on the reading progress and found that while spoilers do not change the degree of reading enjoyment, they reduce interest in continuing to read the story.

Tsang et al. [9] revealed that spoilers reduce the willingness to watch a movie. Johnson et al. [10] showed that while spoilers diminished enjoyment in comedy movies, they increased enjoyment in fantasy and thriller genres. Li et al. [11] investigated the influence of spoilers on box office revenue and its variation over time, finding that



Fig. 1. An image that provides insights to predict the match result.

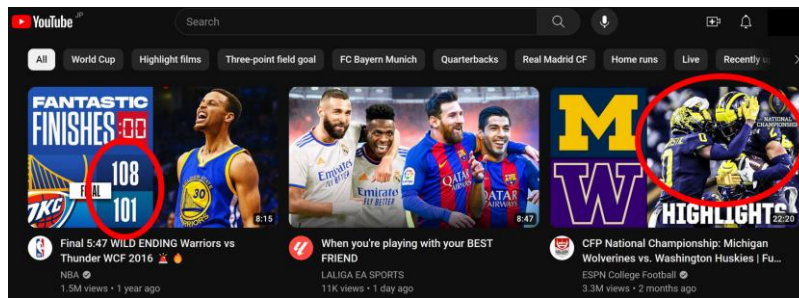


Fig. 2. Encountering spoiler images on YouTube.

spoilers negatively impacted box office revenue only within the first six days after a movie's release.

In sports, Shiratori et al. [2] indicated that spoilers reduce both tension and enjoyment when watching matches. This paper focused on sports spoilers through images.

Regarding the detection of spoilers, Boyd-Graber et al. [12] developed an automatic spoiler detector for social media posts. Golbeck [13] proposed a method to block spoilers related to dramas and sports on Twitter by automatically adding various words to a block list. Nakamura et al. [14] implemented a system that blocks web content, such as sports match results, book reviews, and movie reviews, based on the distribution time of the content. In addition, Wan et al. [15] created a large-scale dataset of book reviews and developed an end-to-end neural network architecture for detecting spoilers in those reviews. Hijikata et al. [16] identified sentences that include story plots in reviews of comics, novels, and movies. They improved the accuracy of identifying story plots by using both contextual and word information.

In sports spoilers, Nakamura et al. [3] proposed a method to block them by making the textual information on websites ambiguous. Jeon et al. [17] also detected Twitter posts containing spoilers about soccer. This paper verified the feasibility of detecting spoiler images in sports to prevent spoilers through images.

2.2 Classification of Sports Images and Videos

Li et al. [18] developed an automatic framework to categorize sports genres, achieving an average accuracy rate of 83% across all 14 sports. Farhad et al. [19] utilized the

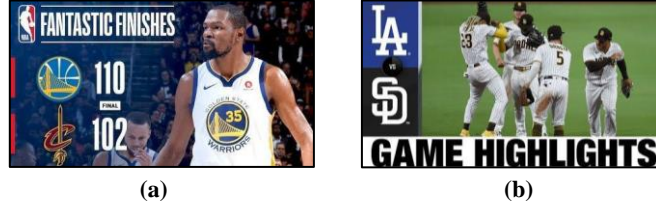


Fig. 3. (a) A direct spoiler image, (b) an indirect spoiler image.

VGG16 transfer learning model to classify images from 18 sports, achieving 93% accuracy. Podgorelec et al. [20] created a dataset of images from four similar sports and proposed an effective method for their classification. In addition, Rafiq et al. [21] utilized a pre-trained AlexNet Convolutional Neural Network for the classification of five different scenes in cricket videos, achieving an accuracy of 99%. Hao et al. [22] successfully identified fine-grained player movements within soccer and basketball highlight reels and demonstrated the potential for classifying detailed scenes such as scoring and fouls.

There has been considerable research on sports image and video classification. While there is the possibility of applying methods from previous research on sports scene classification to detect spoiler images, no method for detecting sports spoiler images has been proposed. This paper analyzes the features of sports spoiler images and proposes methods for their detection.

3 Sports Spoiler Images

3.1 Types of Spoilers

This paper defines sports spoilers as information that enables users to predict match outcomes and reduces their tension and enjoyment of watching recorded matches. Such information can be conveyed not only through text but also through images. For example, Fig. 3 (a) shows the final score of a basketball game, and Fig. 3 (b) captures the scene of players celebrating in a baseball game, indirectly indicating which team won. Thus, due to the difference in the importance of the information conveyed by spoiler images, we categorize sports spoiler images into direct and indirect ones and analyze their features in detail.

We define direct and indirect spoiler images as follows:

- Direct spoiler images: Images that display words related to winning or losing, or the match's final score, directly revealing the match's outcome.
- Indirect spoiler images: Images that allow people to predict the match's outcome based on the players' demeanor.

3.2 Preliminary Investigation of Spoiler Label Annotation

Since there are various types of spoilers, the criteria for determining spoilers vary among individuals. For instance, some consider only showing the final results of a



Fig. 4. Examples of images labeled both “*Would not reduce enjoyment for viewers*” and “*Would definitely reduce enjoyment for viewers*”.

match to be a spoiler, while others perceive that giving information about a player’s performance could be a spoiler, too. To reduce the inconsistency in annotation due to different personal criteria, we conducted a preliminary investigation to unify the criteria for determining spoilers.

We defined spoiler images as images containing information that could spoil viewers’ enjoyment of watching the recorded or delayed broadcasting match. Following our definition, three annotators—two authors and one graduate student who regularly watches sports—annotated images using a web system that we designed. Among the three annotators, one regularly watches baseball, another watches baseball, soccer, and basketball, and the third watches soccer, basketball, and American football. They annotated images by choosing one from three levels of spoilers:

- Would not reduce enjoyment for viewers.
- Might reduce enjoyment for viewers.
- Would definitely reduce enjoyment for viewers.

To verify whether our spoiler image definition standardized spoiler criteria among annotators, we sampled 50 YouTube thumbnails from each of five sports (baseball, soccer, basketball, American football, and volleyball), totaling 250 images, for annotation.

The annotation results revealed an agreement rate of 0.54 among the three annotators. We attributed this low rate to the inadequacy of our definition and the unsuitability of some images as target data. We analyzed images that had greatly divergent labels (both “*Would not reduce enjoyment for viewers*” and “*Would definitely reduce enjoyment for viewers*”) and found many of them were thumbnails of video compilations of individual players’ highlights (see Fig. 4). This was because videos focusing on individual players often covered performances across multiple matches, such as monthly or season highlights, leading to differences in determining whether they constituted spoilers among the annotators.

From these observations, we believed that our definition of spoiler images required modification to reduce subjectivity in annotation. Furthermore, video thumbnails that focus on individual players should be excluded from the dataset.

4 Dataset

4.1 Target Images

Based on the results of our preliminary investigation, we constructed a dataset of sports spoiler images. This paper focused on five popular sports: baseball, soccer, basketball, American football, and volleyball. We also targeted the following YouTube channels covering all teams' matches, including official sports leagues and tournament channels. We collected video thumbnails from these sources using the YouTube Data API.

- Baseball: MLB
- Soccer: Bundesliga, FIFA, LALIGA EA Sports, Serie A
- Basketball: FIBA – The Basketball Channel, March Madness, NBA, WNBA
- American football: ESPN College Football, NFL
- Volleyball: Power Volleyball, Volleyball World

We excluded thumbnails of videos shorter than one minute from our collection target, as many did not relate to the matches' content. We obtained approximately 2,000 images per sport from the above 13 YouTube channels, totaling 10,150 images.

4.2 Spoiler Label Annotation

We revised the definition of spoiler images to images that enabled the prediction of match outcomes. This more precise definition would improve the agreement rate for spoiler annotations. We also modified the levels of spoilers as follows:

- Match outcomes cannot be predicted.
- Match outcomes can be somewhat predicted.
- Match outcomes are clearly predicted.

Additionally, we removed images that focused on individual players and those with low relevance to the match content from the dataset. As a result, the total number of images was reduced to 7,185. Table 1 shows the number of images per sport.

To verify that the label agreement rate among the three annotators would improve, we randomly sampled 100 images from 7,185 images and conducted annotation. The annotators were the same as those mentioned in Section 3.2. As a result of annotation, the agreement rate was improved to 0.87. Based on this result, we determined that the definition of spoiler images and the target images were appropriate, and we annotated the remaining 7,085 images.

Each of the three annotators annotated all 7,185 images using our annotation system (see Fig. 5), resulting in the final label agreement rate of 0.78.

4.3 Proportion of Spoiler Images

To determine the correct labels, we assigned scores according to the level of spoilers:

- 0 points to *Match outcomes cannot be predicted.*
- 1 point to *Match outcomes can be somewhat predicted.*
- 2 points to *Match outcomes are clearly predicted.*

Table 1. Number of images and proportion of spoiler images per sport.

	Baseball	Soccer	Basketball	American Football	Volleyball
Number of images	1,506	1,620	1,405	1,328	1,326
Proportion of spoilers	0.19	0.58	0.20	0.08	0.11

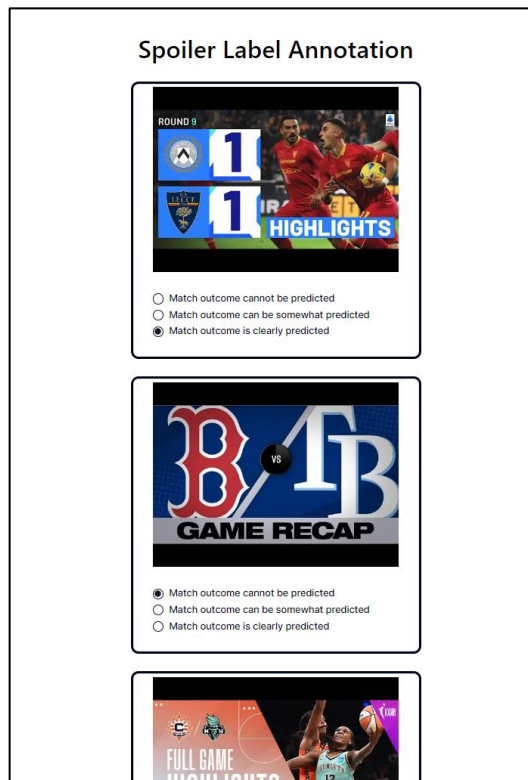


Fig. 5. The spoiler label annotation system.

An image was determined as a spoiler if it received a total spoiler label score of 2 or more from the three annotators and as a non-spoiler if the total score was less than 2.

Following this scoring method, the proportion of spoiler images in our dataset was 0.24. Table 1 indicates that soccer had the highest number of spoiler images, whereas American football and volleyball had significantly fewer. Due to the scarcity of spoiler images in American football and volleyball, we focused on detecting spoilers in the 4,531 images from baseball, soccer, and basketball.



Fig. 6. Examples of spoiler images.



Fig. 7. Examples of non-spoiler images.

Table 2. Proportion of direct and indirect spoiler images per sport.

	Baseball	Soccer	Basketball
Direct spoilers	0.05	0.03	0.30
Indirect spoilers	0.95	0.97	0.70

4.4 Features of Spoiler Images

Fig. 6 illustrates examples of spoiler images, while Fig. 7 shows examples of non-spoiler images. Many direct spoiler images displayed the match’s final score, whereas images that included words related to the outcome, such as *win* or *lose*, were less frequent. Indirect spoiler images often focused on players’ expressions and poses, indicating their joy. In contrast, non-spoiler images typically depicted only team logos, focused equally on players from both teams, and captured moments not crucial to the match outcome.

Based on the definition in Section 3.1, we manually classified spoiler images into direct and indirect spoilers. The classification results showed that the proportion of direct and indirect spoilers varied across sports (see Table 2). Basketball had a higher proportion of direct spoilers compared to other sports, while baseball and soccer had a lower proportion of direct spoilers.

We visually investigated all spoiler images and identified the following features:

- The final match outcome is displayed.
- Players’ expressions include smiling or shouting.
- Players strike poses that express joy or excitement.
- Players from the same team gather to celebrate.

Table 3. Portion of the manually created spoiler dictionary.

Common	Baseball	Soccer	Basketball
happy, success, excite, shout, joy, smile, positive, win, celebrate, embrace	jump, run, big	goal, slip, dive, lead, kneel	fantastic, ending, dramatic, advance

Table 4. Portion of the manually created non-spoiler dictionary.


Common	Baseball	Soccer	Basketball
altercation, brawl, confront, dispute		contest	split-screen, divide, separate, composition

5 Detection Methods

Based on the features of spoiler images described in Section 4.4, this paper proposes the following three methods for detecting spoiler images:

- **Image-Recognition method:** This method employs OCR, emotion assessment, and pose assessment for detecting spoiler images. It uses OCR to identify scores and words associated with match outcomes, emotion assessment to detect facial expressions like smiles or shouting, and pose assessment to recognize poses expressing joy or excitement. An image is classified as a spoiler if any of these features are detected. This method leverages the Google Cloud Vision API for OCR and emotion assessment, and YOLOv8 for pose assessment.
- **Vision-Direct method:** This method employs AI to detect spoiler images. It uses the OpenAI Vision API (using the gpt-4-vision-preview model), configuring the prompt to: *Please analyze this YouTube video thumbnail and determine if it is a spoiler or non-spoiler image. Define a spoiler image as one that reveals the outcome of an event, characterized by the presence of a score or result-related words, players exhibiting emotions of joy or triumph, such as smiling or cheering poses. If the image is a spoiler, respond with 'Spoiler.' If it is a non-spoiler, respond with 'Non-spoiler.' Do not output any other words.* This method uses the API's responses directly as the detection result.
- **Vision-Text method:** This method converts images into text and detects spoiler images based on the textual content. It uses the OpenAI Vision API (using the gpt-4-vision-preview model) to verbalize images and configure the prompt to: *This image is a thumbnail for a YouTube video. Please describe this image.* This method obtains descriptions of the input image and determines whether the image is a spoiler by checking if words in the description match those in a spoiler or non-spoiler dictionary (see Tables 3 and 4). We created the dictionaries by sampling 100 spoiler images and 100 non-spoiler images, respectively, and examining frequently occurring words related to spoiler and non-spoiler features. The dictionaries were constructed by combining words commonly associated with spoiler or non-spoiler features across three sports (baseball, soccer, basketball)

Table 5. An example of OpenAI Vision API’s output in the Vision-Text method. Even in images without any people, words in the spoiler dictionary (in this case, *excitement*) appeared.

Input image	Output text
	<p>The image you’ve provided appears to be a graphic design representing a sports event. This is a thumbnail for a YouTube video about a basketball game. It features the FIBA U20 European Championship logo, suggesting that this is an event for under-20 basketball teams in Europe. The text “FULL GAME QUARTER-FINALS” prominently displayed indicates that the video includes the full coverage of a quarter-final match of the championship. On the left side, there is a basketball with the French flag design, which implies that the French team is one of the competitors in this game. On the right side, there’s another basketball with the colors of the Lithuanian flag, representing Lithuania as the other competing team. The background is dark blue with dynamic blue lines and shapes, giving a sense of motion and excitement which is often associated with sporting events. It’s designed to attract viewers interested in watching the full game from the championship’s quarter-finals between the two national teams.</p>

and those specific to individual sports. The total number of words in the spoiler dictionary is 82, while the total number in the non-spoiler dictionary is 19. Additionally, this method excludes sentences that mention logos or designs to avoid false positives, particularly the risk of images without players being incorrectly identified as spoilers (see Table 5).

6 Evaluation

We assessed the performance of the three methods using the constructed dataset. We employed accuracy, recall, precision, and F1 score as evaluation metrics. In this study, accuracy refers to the proportion of images correctly classified as either spoiler or non-spoiler. Recall indicates the proportion of actual spoilers that are accurately identified, and precision indicates the proportion of identified spoilers that were actually spoilers. Although both precision and recall are important evaluation metrics, this paper particularly emphasizes recall, given the importance of blocking all spoiler information.

Table 6 shows the results of detecting spoiler images using the entire dataset. The Image-Recognition method achieved the highest recall at 0.90, but its precision was the lowest at 0.39. This indicates that the Image-Recognition method determined many images to be spoilers. The Vision-Text method reached a recall of 0.80 and the highest F1 score of 0.78. The Vision-Text method seems to be the most effective for detecting

Table 6. Spoiler detection results for the entire dataset.

	Image-Recognition	Vision-Direct	Vision-Text
Accuracy	0.50	0.83	0.85
Recall	0.90	0.72	0.80
Precision	0.39	0.75	0.76
F1 score	0.55	0.74	0.78

Table 7. Spoiler detection results for baseball.

	Image-Recognition	Vision-Direct	Vision-Text
Accuracy	0.48	0.79	0.86
Recall	0.88	0.71	0.71
Precision	0.25	0.47	0.61
F1 score	0.39	0.57	0.65

Table 8. Spoiler detection results for soccer.

	Image-Recognition	Vision-Direct	Vision-Text
Accuracy	0.69	0.77	0.81
Recall	0.90	0.69	0.83
Precision	0.67	0.89	0.84
F1 score	0.77	0.78	0.83

Table 9. Spoiler detection results for basketball.

	Image-Recognition	Vision-Direct	Vision-Text
Accuracy	0.30	0.92	0.89
Recall	0.92	0.86	0.81
Precision	0.21	0.79	0.69
F1 score	0.35	0.82	0.75

spoiler images. Additionally, the Vision-Direct method showed a recall of 0.72 and an F1 score of 0.74, indicating its potential effectiveness in spoiler detection.

Tables 7, 8, and 9 show the detection results for each sport. In baseball and soccer, the Image-Recognition method achieved the highest recall, while the Vision-Text method reached the highest F1 score. Due to the low precision of the Image-Recognition method, the Vision-Text method appears to be the most effective for detecting spoiler images in baseball and soccer. In basketball, although the Image-Recognition method showed the highest recall, its precision was significantly low. On the other hand, the Vision-Direct method achieved the highest F1 score. Consequently, the Vision-Direct method seems to be the most accurate for spoiler detection in basketball.

These findings suggest that the effectiveness of detection methods can vary depending on the sport.

7 Discussion

7.1 Differences in Detecting Accuracy Across Sports

Across all three detection methods, we observed significant differences in recall and precision among the sports. These differences can largely be attributed to the unique characteristics of each sport, especially in scoring frequency. Specifically, soccer is a sport where scoring is less frequent compared to baseball and basketball, making each point highly significant. As a result, many soccer images depicting scoring moments were annotated as spoilers in our dataset. In contrast, images from baseball and basketball capturing scoring moments were often annotated as non-spoilers because annotators needed to consider additional factors, such as the timing of the score within the match and the number of points scored in the play. This gap led to differences in recall and precision by sport.

7.2 Causes of Misdetection by Each Method

The Image-Recognition method detected poses expressing joy or excitement based on simple spatial relationships, such as wrists and elbows positioned above the shoulders, leading to false positives and reduced precision (see Fig. 8 (a)). Additionally, although this method achieved high recall across all sports, it also produced false negatives due to limited accuracy in emotion assessment (see Fig. 8 (b)).

The Vision-Direct method appears to be effective in detecting spoiler images, as indicated by an F1 score of 0.74 for the entire dataset. In this method, we configured the OpenAI Vision API to provide only detection results. Consequently, we were unable to clarify the specific causes of misdetection (see Fig. 9). Modifying the prompt to include reasons for the detection outcomes could help reveal the causes of misdetection.

The Vision-Text method seems to be the most accurate in detecting spoiler images, but there were some false positives due to reliance on word matching (see Fig. 10 (a)). Specifically, an image was determined as a spoiler if any word from the spoiler dictionary (see Table 3) appeared even once, which led to reduced precision. Furthermore, we found that false negatives occurred due to excluding sentences mentioning logos or designs during preprocessing (see Fig. 10 (b)). Concretely, this exclusion led to the omission of some sentences that referenced scores or match outcomes, resulting in false negatives.

7.3 Future Work

Our detection results might have been influenced by the features of the thumbnails from the YouTube channels used for data collection. Therefore, we aim to expand the dataset of sports spoiler images. Specifically, we plan to increase the variety of sports used for spoiler detection and collect images from sports news sites and social networking services.



Fig. 8. Examples of misdetection in the Image-Recognition method: (a) False positive due to simplistic pose detection, (b) False negative due to incorrect emotion assessment.



Fig. 9. Examples of misdetection in the Vision-Direct method: (a) False positive, (b) False negative. The causes of misdetection could not be identified.



Fig. 10. Examples of misdetection in the Vision-Text method: (a) False positive due to word matching, (b) False negative due to exclusion of sentences mentioning designs.

Additionally, we aim to improve the accuracy of the Vision-Direct and Vision-Text methods. For the Vision-Direct method, we plan to adjust the prompt to output not only the detection results but also the reasons behind the decisions. This adjustment seeks to uncover the causes of misdetection, and we believe that fine-tuning the prompt based on these causes can enhance detection accuracy. As for the Vision-Text method, we expect that accuracy will increase by including sentences that mention designs and by evaluating the number and frequency of words from the spoiler or non-spoiler dictionary in OpenAI Vision API's responses to determine spoiler images.

8 Conclusion

In this paper, to prevent sports spoilers through images, we verified the feasibility of detecting spoiler images. We specifically focused on YouTube thumbnails for sports content, defining spoiler images as images that enable the prediction of match outcomes. We constructed and analyzed a dataset of sports spoiler images and proposed three detection methods.

Upon evaluating the performance of our methods with the entire dataset, the Vision-Text method appears to be the most effective for detecting spoiler images. However, the most effective method and detection accuracy might vary depending on the sport type.

Our future work will aim to include a wider range of sports and expand the dataset by collecting images from various media, including news sites and social networking services. Additionally, we intend to enhance the detection accuracy of both the Vision-Direct and Vision-Text methods.

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