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ARTICLE

# Improved Hashtag Recommendation Algorithm Determining Appropriate Hashtags for Words with Different Meanings

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## Abstract
In image-posting social networking services, such as Instagram, recommendation of appropriate hashtags for posts is vital. In the existing methods, a hashtag is searched using the names of object labels included in images added to posts as hashtags, and a relevance prediction model is applied to hashtags that appear most frequently among those attached to posts obtained from the search. Hashtags that are considered highly relevant to the post are then recommended to the user. However, it is difficult to recommend adequate hashtags relevant to a post containing a label that refers to different objects, such as "mouse," which can refer to a "computer input device" and an "animal." In this study, we developed algorithms (Algorithms 1 and 2) that employ additional labels related to object labels in posts to solve this problem. As additional labels, Algorithm 1 uses the other labels in the same object category in the Microsoft Common Objects in Context (COCO) image database, and Algorithm 2 uses words translated into six other languages. We also developed Algorithm 3, which is a hybrid of Algorithms 1 and 2. Based on user questionnaires, the hashtags suggested by Algorithms 1 and 2 are highly relevant to the posts: compared to an existing algorithm, the relevance of the hashtags improved by 18% and 64%, respectively.

**Keywords** Hashtag · Social network service (SNS) · Common objects in context · Recommendation · Different meaning · Co-occurrence

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## 1 Introduction

In image-posting social networking services (SNS), such as Instagram, users add multiple hashtags to a single post to improve the searchability of images for other users. However, in many Instagram posts, there is a mismatch between the images and the added hashtags. This mismatch can be a result of several reasons, including intentional mislabeling, where users add popular but irrelevant hashtags to attract more views, and unintentional mislabeling, where users mistakenly use incorrect hashtags or fail to accurately describe the content. Yui et al. [1] referred to such misleading posts as "clickbait." Cho et al. [2] stated that the effective use of hashtags requires adequate and relevant hashtags, which limits the diversity of hashtags. According to Fedushko et al. [3], "hashtags should always correspond to the subject of the post." Therefore, when posting an image, it is crucial to choose hashtags that are "highly relevant" to the post to ensure that the content is represented accurately and easily discovered by other users. Misleading or irrelevant hashtags can reduce user satisfaction and engagement, as well as poster credibility.

Several studies have proposed "highly relevant" hashtags based on data from Twitter and other sources. Takenaka et al. [4] proposed a method for selecting appropriate hashtags for tweets using Bayesian inference. Zangerle et al. [5] proposed a method that recommends hashtags based on similar tweets and the hashtags used. In this method, the similarity between tweets and hashtags on Twitter is evaluated using term frequency-inverse document frequency (TF-IDF). Godin et al. [6] developed a method that extracts topics containing the body of tweets and related URL information based on which hashtags are suggested. Kywe et al. [7] considered user preferences and tweet content to suggest hashtags. Liu et al. [8] developed a word trigger method that recommends hashtags based on a large set of hashtag-sentence pairs. Ding et al. [9] proposed a method that suggests hashtags based on the Chinese microblog Sina-Weibo by learning a topic model.

In a previous study, the authors proposed a method for predicting the relevance of Instagram hashtags and posts [10]. First, an object detection algorithm is used to obtain the label of an object that appears in an image included in an image-posting SNS. Then, an Instagram hashtag search is performed using the object label as the hashtag to retrieve the posts. The comments are also extracted from the obtained posts and hashtags. Using the hashtags, variables, including reverse co-occurrence count, reverse co-occurrence ranking, and similarity between comments, are defined. These variables are then used to create a hashtag-post relevance prediction model. By extracting hashtags that co-occur with object labels from the retrieved posts, many hashtags that are highly related to the object labels can be obtained. Ichau et al. [11] also discovered themes related to a specific hashtag by performing co-occurrence network analysis on 1500 Instagram posts containing specific hashtags.

However, the algorithms proposed in the above-mentioned studies cannot obtain "highly relevant" hashtags for a post from a label referring to different objects, such as "mouse," which can refer to "an animal" or "a computer input device." Among the 91 categories in the Microsoft Common Objects in Context (COCO) dataset, there are five such labels:"spoon," "bear," "mouse," "keyboard," and "train." In this case, hashtags related to any meaning can be retrieved from Instagram, resulting in ambiguity and poor search accuracy.

Accurate hashtag recommendations are crucial for improving the searchability of images on SNSs, like Instagram. Without relevant hashtags, it would be difficult for users to find the images they are looking for, which reduces user satisfaction and engagement. To address this search problem, we developed three algorithms that enhance the relevance of recommended hashtags.

Algorithm 1 uses the same object category from the Microsoft COCO image dataset as additional labels to retrieve the label of an object contained in a post. Algorithm 2 uses the word translated into six other languages as additional labels, and Algorithm 3 is a hybrid of Algorithms 1 and 2. The proposed algorithms disambiguate labels with multiple meanings and provide more accurate hashtag recommendations.

The remainder of this paper is organized as follows: Sect. 2 introduces the algorithm proposed in a previous study, and Sect. 3 introduces the proposed algorithms. Section 4 describes the experiments, and Sect. 5 discusses the results. Section 6 concludes the paper.

## 2 Existing Algorithms

Herein, we present the algorithms proposed in previous studies for comparison.

### 2.1 Overview of the Existing Hashtag Recommendation System

Figure 1 shows a schematic of the algorithm proposed in a previous study [10]. The terms "co-occurrence counts," "reverse co-occurrence counts," "reverse co-occurrence ranking values," and "similarity between comments" in the procedure are explained in the section 2.2. The numbers on the diagram correspond to the order numbers of the algorithm process. The algorithm functions as follows:

1. A user inputs the image.
2. The object detection algorithm YOLO [12] is applied to the image to obtain the labels of the object $L$ contained in the image. In cases where the algorithm uses the Microsoft COCO dataset [13], 91 object labels are considered as candidates for $L$.
3. Instagram posts are searched using $L$ as a hashtag.
4. Let $P$ be a set of posts obtained by hashtag search.
5. Let $C$ be the set of all comments in $P$.
6. Let $H$ be the set of hashtags attached to $C$.

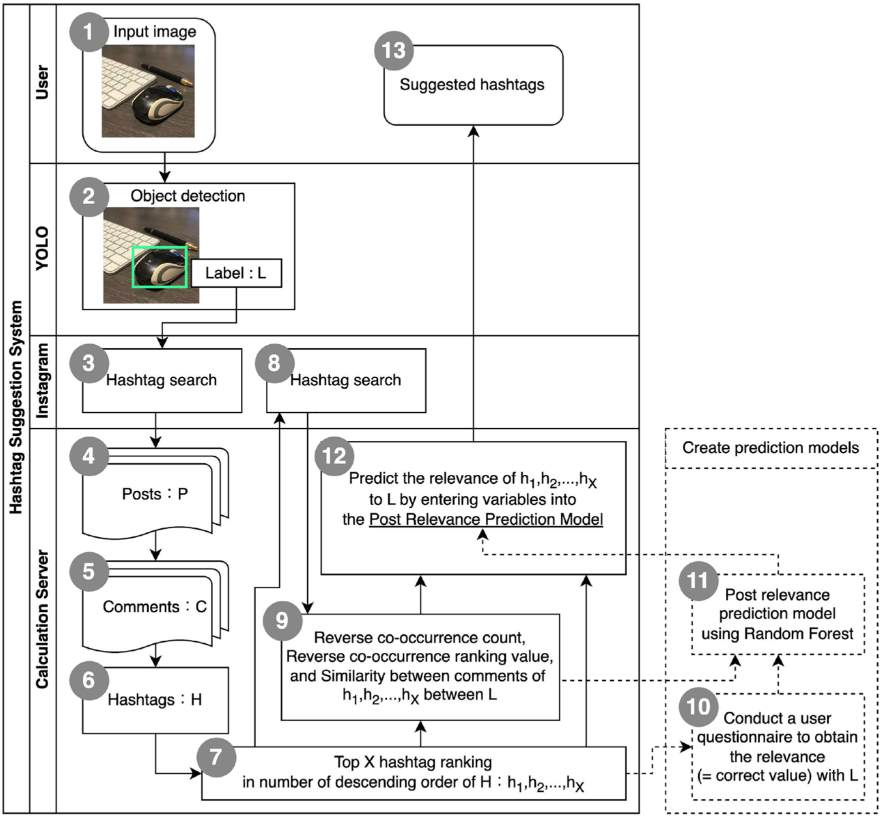


**Fig. 1** Schematic of the hashtag recommendation algorithm proposed in a previous study [10]. The numbers in this figure correspond to the process descriptions

7. Elements of $H$ are sorted in decreasing order of co-occurrence counts. The variable $H = \{h_j\} = \{h_1, h_2, \ldots, h_X\}$ denotes the top $X$ hashtags in the $H$ hashtag ranking, excluding the object label $L$.
8. Instagram posts are searched using $H$ as a hashtag.
9. The number of reverse co-occurrence counts, reverse co-occurrence ranking, and similarity between comments [10] with $L$ for each $H$ are calculated using posts retrieved in the previous process.
10. A user questionnaire is conducted to collect the relevance of $H$ to $L$.
11. A post's relevance prediction model is created using a random forest with relevance as the correct answer value and reverse co-occurrence count, reverse co-occurrence ranking, and similarity between comments as the explanatory variables (these are represented by dotted lines in Fig. 1).
12. Using these variables, a hashtag-post relevance prediction model is applied to $H$, and hashtags that are considered "highly relevant" to the post are decided.
13. Finally, hashtags considered "highly relevant" to the post are recommended to the user as suggested hashtags.

## 2.2 Terms Used in the Algorithm

In this section, we explain the terms "co-occurrence count," "reverse co-occurrence count," "reverse co-occurrence ranking value," and "similarity between comments" used in the above-mentioned algorithm.

### 2.2.1 Co-occurrence Count

In the hashtag $H$ included in Fig. 1, the number of occurrences of each hashtag is the co-occurrence count, and its ranking is the co-occurrence count ranking.

For example, the top 10 co-occurrence counts $h_1, h_2, \dots, h_{10}$ obtained using the label "mouse" are shown in Fig. 2. The horizontal and vertical axes represent the number of occurrences and co-occurrence counts of the hashtag, respectively. The top three hashtags based on the co-occurrence counts for the hashtag "mouse" are $h_1$ ="#gaming", $h_2$="#cute", and $h_3$="#mousepad."

### 2.2.2 Reverse Co-occurrence Count

For each hashtag $H$ with a label $L$ in Fig. 1, hashtags are retrieved, and co-occurrence ranking is established. The number of occurrences of label $L$ in the ranking is the reverse co-occurrence count of the hashtag.

### 2.2.3 Reverse Co-occurrence Ranking Value

For each $H$ with a label $L$ in Fig. 1, hashtags are retrieved, and a co-occurrence ranking is established. The rank of label $L$ in the ranking is the reverse co-occurrence ranking value.

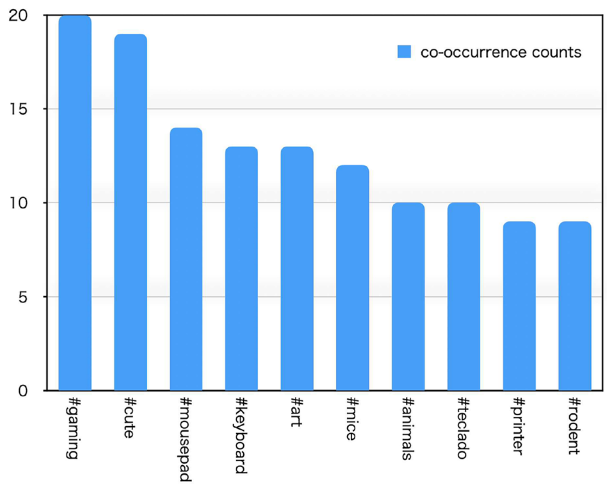


**Fig. 2** Co-occurrence count ranking for the hashtag "mouse"

#### 2.2.4 Similarity Between Comments

The label $L$ is used to retrieve comments $C$ in Fig. 1, and the label $H$ is used to retrieve comments $C' = \{C_j\} = \{C_1, C_2, \dots, C_X\}$.

Let $N$ be the number of words that appear in$C$ or $C'$; all words are then represented as $\{t_i\} = \{t_1, t_2, \dots, t_N\}$. Where $n_{i,j}$ is the number of occurrences of the word $t_i$ in the comments $C_j$, $\Sigma_k n_{k,j}$ is the sum of the occurrences of all words in the comments $C_j$, $|C|$ is the number of comments, and $|\{C : C \ni t_i\}|$ is the number of comments containing the word $t_i$, the TF-IDF of the word $t_i$ in each comment is calculated as follows:

$$\mathrm{tf} - \mathrm{idf}_{i,j} = \mathrm{tf}_{i,j} \cdot \mathrm{idf}_i \tag{1}$$

$$\mathrm{tf}_{i,j} = \frac{n_{i,j}}{\sum_k n_{k,j}} \tag{2}$$

$$\mathrm{idf}_i = \log \frac{|C|}{\left|\left\{C : C \ni t_i\right\}\right|} \tag{3}$$

Finally, if the TF-IDF values of the word vector for the comments $C$ and $C_j$ are given as $a$ and $b$, respectively, their cosine, which is the similarity between comments of $h_j$ to $L$ is calculated as follows:

$$a = \left\{a_1, a_2, \dots, a_N\right\} \tag{4}$$

$$b = \left\{b_1, b_2, \dots, b_N\right\} \tag{5}$$

$$\cos\theta = \frac{\sum_{k=1}^{N} a_k b_k}{\sqrt{\sum_{k=1}^{N} a_k^2}\sqrt{\sum_{k=1}^{N} b_k^2}} \tag{6}$$

## 3 Proposed Algorithm

In the bove-decribed algorithm, when the object label $L$ is a word referring to different objects, the hashtag $H$ often includes hashtags that are less relevant to $L$. For example, if the object label $L$ is “mouse”, the hashtags $H$ includes the hashtags related to not only “mouse” as a computer input device but also an animal. Herein, we propose three algorithms to solve this problem.

### 3.1 Algorithm 1

Algorithm 1 employs labels belonging to the same object category in the Microsoft COCO dataset. There are 91 object labels in the Microsoft COCO dataset, which belong to the following categories: Person, Accessory, Animal, Vehicle, Outdoor Objects, Sports, Kitchenware, Food, Furniture, Appliance, Electronics, and Indoor objects.

Algorithm 1 collects submissions for the object label *L* using labels that belong to the same category. For example, in the category "Electronics," there are six category labels: "tv," "laptop," "mouse," "remote," "keyboard," and "cellphone." The five category names "tv," "laptop," "remote," "keyboard," and "cellphone" are used to create a co-occurrence count ranking for "mouse." Figure 3 shows a schematic of Algorithm 1. The part processes indicated by bold lines differ from the algorithm depicted in Fig. 1.

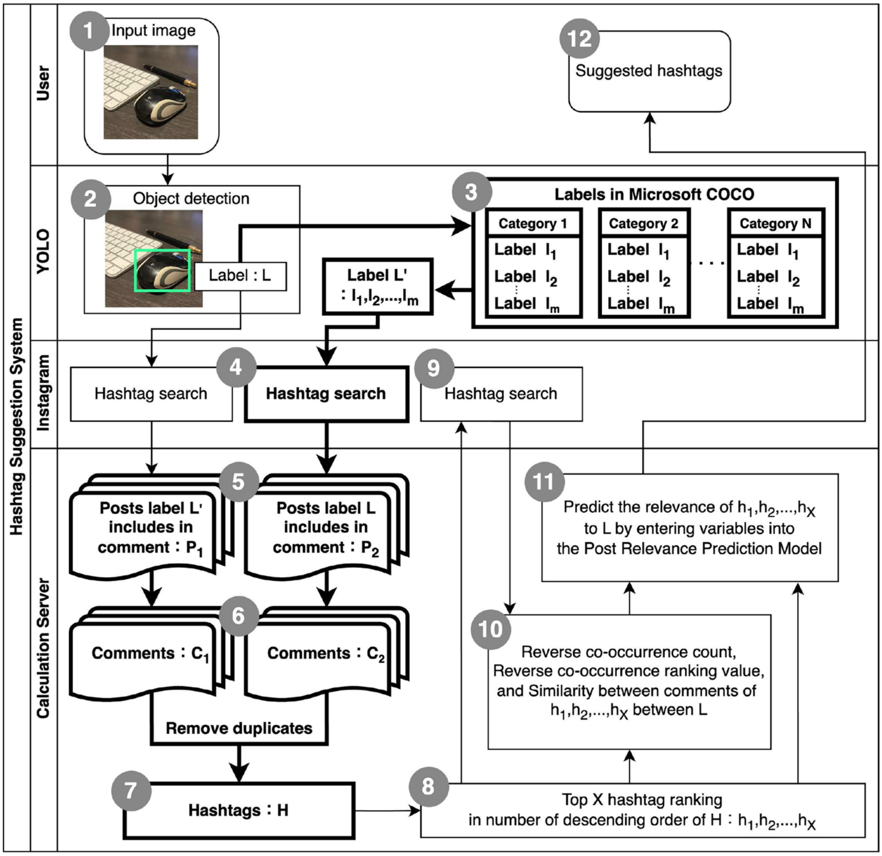


**Fig. 3** Schematic of Algorithm 1. Parts of the algorithm that differ from those in Fig. 1 are indicated by bold lines. The numbers in this figure correspond to the process descriptions

The process of Algorithm 1 is summarized as follows. The numbers in the diagram correspond to the numbers of the algorithm process.

1. A user inputs the image.
2. The object detection algorithm YOLO [12] is applied to the input image to obtain the label $L$ of the object contained in the image. s
3. A label $L' = \{l_1, l_2, \dots, l_m\}$ that belongs to the same category as label $L$ in the Microsoft COCO dataset is obtained. Here, $m$ is the number of labels excluding $L$ that are in the same category as $L$.
4. Instagram posts are searched using $L$ and $L'$ as hashtags.
5. Let $P_1$ be the set of posts in which $L'$ is included as a hashtag in the comments on posts and $P_2$ be the set of posts in which $L$ is included as a hashtag in the comments of posts.
6. Let $C_1$ and $C_2$ be the sets of comments obtained from $P_1$ and $P_2$, respectively.
7. After removing duplicates of $C_1$ and $C_2$, $H$ is the set of all hashtags attached to the comments.
8. The elements of $H$ are sorted in decreasing order of co-occurrence counts. Variable $H = \{h_j\} = \{h_1, h_2, \dots, h_X\}$ denote the top $X$ hashtags in the $H$ hashtag ranking, excluding the object label $L$.
9. Instagram posts are searched using the hashtag $H$.
10. The reverse co-occurrence count, reverse co-occurrence ranking, and similarity between comments with $L$ for each $H$ are calculated using the posts retrieved in the previous step.
11. Using these variables, a hashtag-post relevance prediction model is applied to $H$, and hashtags considered "highly relevant" to the post are decided.
12. The "highly relevant" hashtags are recommended to the user as suggested hashtags.

### 3.2 Algorithm 2

Algorithm 2 employs a translation term for each label.

The labels of the Microsoft COCO dataset that are considered candidates for $L$ are in the English language. Algorithm 2 uses the translated word for $L$ into a language other than English as a candidate for $L'$. The target languages based on the number of language users in the world and the number of Instagram users are as follows.

- Hindi
- Portuguese
- Indonesian
- Russian
- Turkish
- Japanese.

For example, when the object label $L$ is "spoon", the candidates for $L''$ are translated into चम्मच in Hindi, "colher" in Portuguese, "sendok" in Indonesian, "ложка" in Russian, "kaşık" in Turkish and "スプーン" in Japanese.

Figure 4 shows a schematic of Algorithm 2. The parts indicated by bold lines differ from those of the algorithm depicted in Fig. 1.

The process of Algorithm 2 is summarized as follows. The numbers in the diagram correspond to the numbers in the algorithm process.

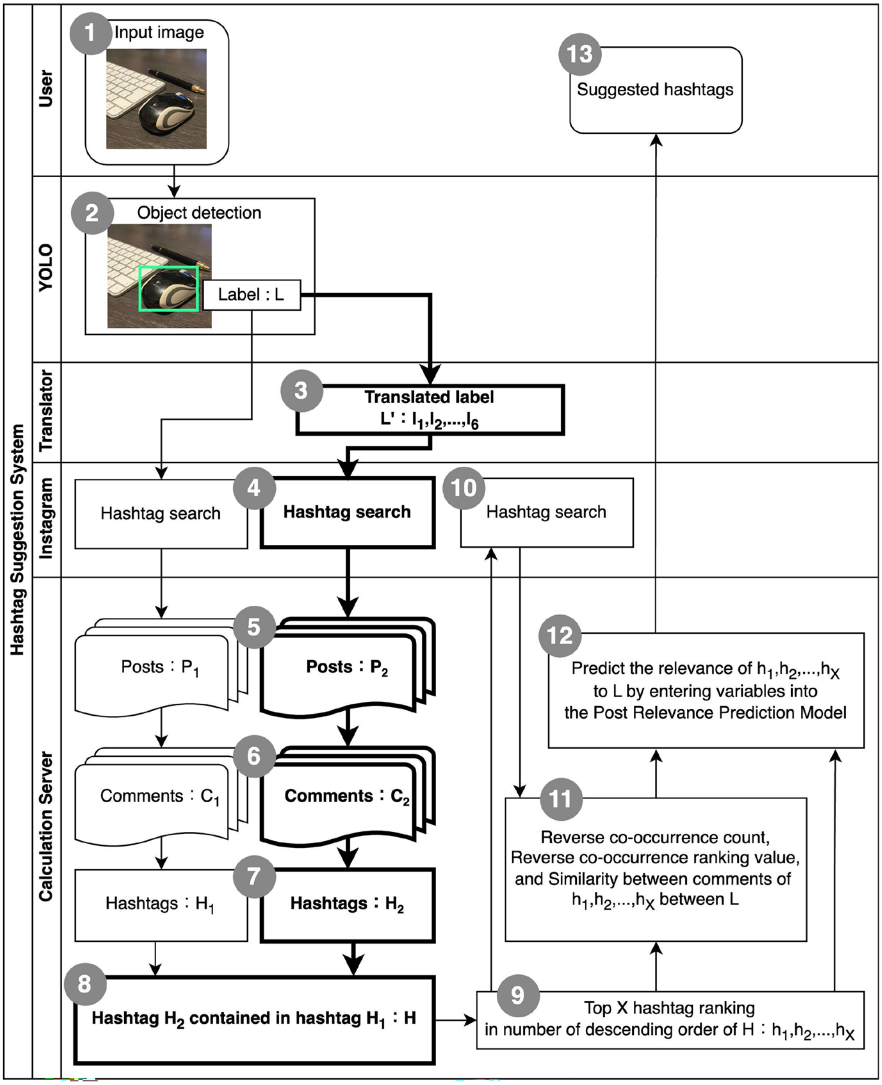


**Fig. 4** Schematic of Algorithm 2. The parts of the algorithm that differ from those in the algorithm depicted in Fig. 1 are indicated with bold lines. The numbers in this figure correspond to the process descriptions of the algorithm

1. A user inputs the image.
2. The object detection algorithm YOLO [12] is applied to the input image to obtain the label $L$ of the object contained in the image.
3. Let $L' = \{l_1, l_2, \dots, l_6\}$ be the six translations of label $L$.
4. Instagram posts are searched using $L$ and $L'$ as a hashtag.
5. Let $P_1$ be the set of posts on Instagram obtained using the label $L$ as a hashtag and $P_2$ denote the set of Instagram posts obtained using the label $L'$ as the hashtag.
6. Let $C_1$ and $C_2$ be the sets of comments obtained from $P_1$ and $P_2$, respectively.
7. Let $H_1$ and $H_2$ be the sets of all hashtags attached to $C_1$ and $C_2$, respectively.
8. A set of $H_2$ hashtags in $H_1$ is extracted and denoted as $H$.
9. The elements of $H$ are sorted in decreasing order of co-occurrence counts. Variable $H = \{h_j\} = \{h_1, h_2, \dots, h_X\}$ denote the top $X$ hashtags in the $H$ hashtag ranking, excluding the object label $L$.
10. Posts on Instagram are searched using the hashtag $H$.
11. The number of reverse co-occurrence counts, reverse co-occurrence ranking, and similarity between comments with $L$ for each $H$ are calculated using the posts retrieved in the previous step.
12. Using these variables, a hashtag-post relevance prediction model is applied to $H$, and hashtags considered "highly relevant" to the post are decided.
13. Finally, the "highly relevant" hashtags are recommended to the user as suggested hashtags.

### 3.3 Algorithm 3

This section describes the proposed Algorithm 3, which is a hybrid of Algorithms 1 and 2. Algorithm 3 leverages the strengths of Algorithms 1 and 2 to improve the relevance of suggested hashtags using both category- and translation-based approaches.

Figure 5 shows a schematic of Algorithm 3. The process of the algorithm is summarized as follows. Here, $X$ is only assumed to be an even number.

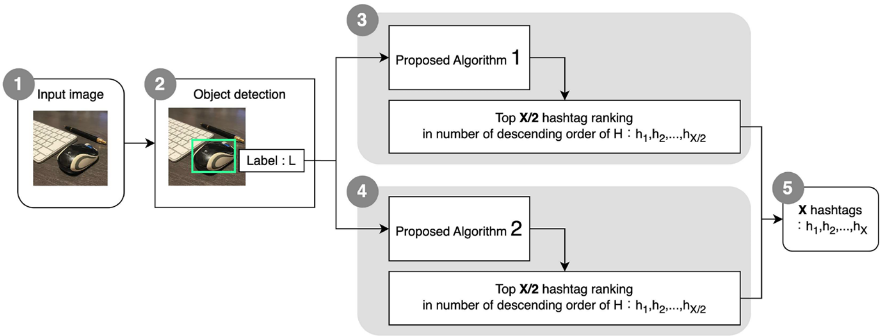


**Fig. 5** Schematic of Algorithm 3. The top and bottom parts show the processes of Algorithms 1 and 2, respectively. The final output combines the top $X/2$ hashtags from each algorithm to form the final set of $X$ hashtags

1. A user inputs the image.
2. The object detection algorithm YOLO [12] is applied to the input image to obtain a label $L$ for the object in the image.
3. The label $L$ is used to run Algorithm 1 to obtain $H = \{h_j\} = \{h_1, h_2, \dots, h_{X/2}\}$, which is the top $X/2$ hashtags in the $H$ hashtag ranking, excluding the object label $L$.
4. The label $L$ is used to run Algorithm 2 to obtain $H = \{h_j\} = \{h_1, h_2, \dots, h_{X/2}\}$, which is the top $X/2$ hashtags in the $H$ hashtag ranking, excluding the object label $L$.
5. The top $X/2$ hashtags from each algorithm are combined to create a set of $X$ hashtags.

## 4 Experiment

This study aims to obtain a set of hashtags that are "highly relevant" to a post from a label that refers to different objects. Therefore, the co-occurrence frequency ranking of the algorithm proposed in a previous study and that of Algorithms 1, 2, and 3 were used to obtain the top $X$ hashtags $H$, excluding object labels $L$, and the relevance value, which represents the relevance between hashtags and posts for compoarison.

### 4.1 Determination of the Label *L*

To validate the effectiveness of the proposed algorithms, we assume that object labels are pre-determined by object recognition using YOLO.

First, a hashtag search is conducted on Instagram using each of the 91 Microsoft COCO dataset categories as a label. After checking the top 30 new posts and finding at least 10 posts that refer to different objects in the Microsoft COCO dataset categories, the labels "spoon", "bear", "mouse", "keyboard", and "train" are selected as the labels $L$ to be used in the experiment. Different objects used on Instagram and the meaning of each label $L$ in object detection based on the Microsoft COCO dataset, which is the correct value in this study, are listed in Table 1.

**Table 1** Meanings of the labels "spoon", "bear", "mouse", "keyboard", and "train" used on Instagram and their labels recognized by YOLO based on the Microsoft COCO dataset

| | Meanings | Labels in the Microsoft COCO dataset |
|---|---|---|
| spoon | Eating or cooking utensils, car models | Eating or cooking utensils |
| bear | Bears as animals, beard | Bears as animals |
| mouse | Computer input device, mouse as animal | Computer input device |
| keyboard | Computer input device, piano keyboard | Computer input device |
| train | Train as a vehicle, muscle training | Train as a vehicle |

### 4.2 User Questionnaire

Herein, we discuss the relevance of the label $L$ and the top 30 hashtags $H = \{h_1, h_2, \ldots, h_{30}\}$ in terms of co-occurrence frequency for the label $L$ to validate the proposed algorithm.

We administered a questionnaire to 15 subjects. For each of the five labels "spoon", "bear", "mouse", "keyboard", and "train," the four algorithms were used to obtain the top 30 hashtags with the highest number of co-occurrences. For each of the 450 hashtags obtained, subjects were asked to rate the relevance between the label $L$ (object recognition label from the Microsoft COCO dataset in Table 1) and the hashtags in three levels (high, medium, and low). Let $R_j$ be the number of subjects who selected "high" for hashtag $h_j$, $S_j$ the number of subjects who selected "medium", and $T_j$ the number of subjects who selected "low." The subjects were asked to choose "unknown" when it is difficult for them to determine the relevance of the hashtag.

The responses "high", "medium", and "low" or "unknown" were assigned values of 1, 0.5 and 0, respectively. The relevance $r_j$ of the hashtags was calculated as follows.

$$r_j = (R_j + 0.5 \cdot S_j)/15 \tag{7}$$

### 4.3 Results

For the five labels, "spoon", "bear", "mouse", "keyboard", and "train", the results of the questionnaire for a total of 150 hashtags in the top 30 co-occurrences obtained using the algorithms were compared.

The average relevance values for the labels of hashtags with the top 10 and 30 co-occurrence counts are listed in Tables 2 and 3, respectively. For each hashtag, the largest relevance value is written in bold, and the second largest value is underlined.

Compared to the previous algorithm, the relevance of the hashtags increased by 59% for Algorithm 1 (from 0.29 to 0.46) and 45% for Algorithm 2 (from 0.29 to 0.42), as shown in Table 2. Except for the word "keyboard", Algorithm 3 shows the second-best results, indicating that the hybrid algorithm outperforms the individual algorithms in predicting hashtags regardless of the word.

**Table 2** Average relevance of postings to hashtags with the top 10 co-occurrence counts obtained for the label $L$ using the previous and proposed algorithms

| L | spoon | bear | mouse | keyboard | train | average |
|---|---|---|---|---|---|---|
| Previous algorithm | 0.03 | 0.28 | 0.32 | **0.60** | 0.24 | 0.29 |
| Proposed algorithm 1 | 0.46 | **0.72** | **0.54** | <u>0.52</u> | 0.04 | **0.46** |
| Proposed algorithm 2 | **0.58** | 0.30 | 0.08 | 0.37 | **0.75** | 0.42 |
| Proposed algorithm 3 | <u>0.55</u> | <u>0.53</u> | <u>0.33</u> | 0.45 | <u>0.37</u> | <u>0.45</u> |

For each label, the largest relevance value is in bold and the second largest value is underlined

**Table 3** Average relevance of postings to hashtags with the top 30 co-occurrence counts hashtags obtained for the label *L* using the previous and the proposed algorithms

| L | spoon | bear | mouse | keyboard | train | average |
|---|---|---|---|---|---|---|
| Previous algorithm | 0.04 | 0.49 | <u>0.29</u> | **0.53** | 0.26 | 0.28 |
| Proposed algorithm 1 | 0.31 | **0.60** | **0.49** | 0.45 | 0.07 | 0.33 |
| Proposed algorithm 2 | **0.52** | 0.27 | 0.11 | <u>0.47</u> | **0.75** | **0.46** |
| Proposed algorithm 3 | <u>0.51</u> | <u>0.57</u> | 0.27 | 0.39 | <u>0.43</u> | <u>0.43</u> |

For each label, the largest relevance value is indicated in bold, and the second largest value is underlined

Similarly, for hashtags with the top 30 co-occurrence counts (Table 3) compared with the preivious algorithm, the average relevance of the hashtags predicted by Algorithms 1 and 2 increased by 18% (from 0.28 to 0.33) and 64% (from 0.28 to 0.46), respectively. Except for the words “mouse" and “keyboard", Algorithm 3 exhibited the second-best results, indicating that Algorithm 3 outperforms Algorithms 1 or 2 in predicting hashtags regardless of the word.

For the labels “spoon,” “bear,” and “mouse,” the relevance values obtained using Algorithm 1 in both cases of top 10 and 30 co-occurrence counts were higher than those obtained by the previous algorithm. In contrast, the relevance value obtained for the label “train” using Algorithm 2 was significantly higher than that obtained by the previous algorithm. However, the values for the labels “mouse” and “keyboard” in the top 10 co-occurrence counts and for “bear”, “mouse”, and “keyboard” in the top 30 co-occurrence counts were lower than those of the previous algorithm. For the label “spoon,” the relevance values obtained by Algorithms 1 and 2 were significantly higher than those obtained by the previous algorithm.

Algorithm 3 exhibited minimum relevance values of 0.33 and 0.27 for the hashtags with the top 10 and 30 co-occurrence counts, respectively. For all labels, Algorithm 3 exhibited no significantly low values.

Tables 4 and 5 list the relevance values for the top 10 hashtags in terms of co-occurrence counts for the labels “spoon” and “train.”

**Table 4** Top 10 hashtags in terms of co-occurrence counts and relevance value for “spoon” using the previous and proposed algorithms

| | Previous algorithm | | Proposed algorithm 1 | | Proposed algorithm 2 | |
|---|---|---|---|---|---|---|
| 1 | #honda | 0.03 | #fork | 0.70 | #handmade | 0.83 |
| 2 | #jdm | 0.03 | #food | 0.90 | #wood | 0.70 |
| 3 | #mugen | 0.00 | #knife | 0.67 | #woodwork | 0.67 |
| 4 | #hondacivic | 0.03 | #photo | 0.03 | #craft | 0.57 |
| 5 | #civic | 0.00 | #personaltouch | 0.07 | #sloyd | 0.37 |
| 6 | #vtec | 0.03 | #disposable | 0.20 | #woodenspoon | 1.00 |
| 7 | #spoonsports | 0.17 | #plates | 0.63 | #instagood | 0.23 |
| 8 | #typer | 0.00 | #trending | 0.03 | #likeforlikes | 0.17 |
| 9 | #ek9 | 0.03 | #home | 0.57 | #spooncarving | 0.90 |
| 10 | #usdm | 0.00 | #kitchen | 0.83 | #vintage | 0.40 |

**Table 5** Top 10 hashtags in terms of co-occurrence counts and relevance value for "train" using the existing and proposed algorithm

| | Previous algorithm | | Proposed algorithm 1 | | Proposed algorithm 2 | |
|---|---|---|---|---|---|---|
| 1 | #fitness | 0.03 | #health | 0.03 | #railfans | 0.97 |
| 2 | #health | 0.03 | #cardio | 0.03 | #railway | 1.00 |
| 3 | #railway | 0.97 | #workout | 0.00 | #photography | 0.23 |
| 4 | #workout | 0.00 | #fitness | 0.03 | #keretaapikita | 0.63 |
| 5 | #training | 0.10 | #fit | 0.03 | #keretaapiindonesia | 0.70 |
| 6 | #photooftheday | 0.10 | #fitnessaddict | 0.03 | #travel | 0.90 |
| 7 | #fit | 0.03 | #training | 0.10 | #railfan | 0.97 |
| 8 | #photography | 0.13 | #strong | 0.03 | #trainspotting | 0.60 |
| 9 | #trains | 1.00 | #getfit | 0.03 | #trainspotter | 0.80 |
| 10 | #gym | 0.03 | #gym | 0.03 | #ferrovia | 0.67 |

**Table 6** Discussion of each label in Algorithm 1

| *L* | Effect | Discussion |
|---|---|---|
| spoon | ↗ | Hashtags related to the Kitchenware category are lined up |
| bear | ↗ | A large increase in hashtags related to "panda" |
| mouse | ↗ | Most hashtags are related to computer accessories |
| keyboard | → | Music-related hashtags disappear but printer-related hashtags being judged "lower relevant" |
| train | ↘ | Mostly related to "muscle training" |

The transition in the relevance value from the previous algorithm is indicated by arrows in the effect column

**Table 7** Discussion for each label in Algorithm 2

| *L* | Effect | Discussion |
|---|---|---|
| spoon | ↗ | Hashtags describe a more specialized "spoon" |
| bear | ↘ | The Portuguese word "urso" means not only "bear" but also "male" |
| mouse | ↘ | Translations have the meaning of both "computer input device" and "mouse as animal" |
| keyboard | → | Translations have the meaning of both "computer input device" and "piano keyboard" |
| train | ↗ | Almost all hashtags related to trains |

The transition in the relevance value from the previous algorithm is indicated by arrows in the effect column

# 5 Discussion

Tables 6 and 7 summarize the results of Algorithm 1 and 2 for each label *L*.

## 5.1 Spoon

For the label "spoon," the top 10 hashtags obtained by the algorithm proposed in the previous study in terms of co-occurrence counts mostly represent car models or manufacturers, as shown in Table 1. However, the ranking established by Algorithms 1 and 2 includes many hashtags related to tools for eating or cooking, which correspond to "labels in the Microsoft COCO dataset" in Table 1. Algorithm 1 uses labels in the same object category in the Microsoft COCO dataset. Therefore, hashtags related to the category Kitchenware, such as "#fork," "#knife," and "#kitchen," were obtained, as shown in Table 4. Alternatively, Algorithm 2 uses a translation term; thus, it retrieved hashtags that describe more specialized "spoon," such as "#handmade," "#woodenspoon," and "#spooncarving," as shown in Table 4.

## 5.2 Train

For the label "train," the top 10 hashtags predicted by the previous algorithm and Algorithm 1 are mostly related to "muscle training," as shown in Table 1.

The average relevance of hashtags predicted by Algorithm 1 decreased, whereas that of hashtags predicted by Algorithm 2 increased significantly compared to the value for the previous algorithm. The decrease in the average relevance of the hashtags predicted by Algorithm 1 can be attributed to the high number of Instagram posts with the hashtag "#car" and hashtags related to "muscle training." Algorithm 2, which uses "train" translated into various languages, did not consider "car" as a label. Thus, it could suggest more hashtags related to "train."

## 5.3 Mouse

The average relevance of the hashtags predicted by Algorithm 2 for the label "mouse" was significantly lower than that of the previous algorithm, which is primarily because the translations also have the meanings of both "computer input device" and "animal." Algorithm 1 overcomes this challenge by using labels that belong to the same object category "Electronics" in the Microsoft COCO dataset. Therefore, the average relevance of the predicted hashtags was significantly high.

## 5.4 Keyboard

The music-related hashtags predicted by the previous algorithm disappeared in Algorithm 1. However, there were no significant changes in the average relevance of the predicted hashtags because the relevance of printer-related hashtags was ranked as "low" by the subjects. In Algorithm 2, similar to the case of the label "mouse," music-related hashtags were also retrieved because the translations have the meanings of both "computer input device" and "piano keyboard."

### 5.5 Bear

The average relevance of the hashtags predicted by Algorithm 2 for "bear" was low for the top 30 cooccurrences because the Portuguese word "urso" means not only "bear" but also "male." In contrast, the hashtags predicted by Algorithm 1 exhibited higher average relevance values due to the numerous hashtags related to "panda."

## 6 Conclusion

Users of image-posting SNSs, such as Instagram, add multiple hashtags to a single post to improve image searchability by other users. However, there is a mismatch between several Instagram posts and the added hashtags. Accurate and relevant hashtags are essential for the effective use of such social media platforms; thus, there is a need to predict "highly relevant" hashtags.

An algorithm proposed in previous studies could not obtain a "high relevance" co-occurrence count ranking for labels like "mouse" due to its multiple meanings (e.g., an "animal" and a "computer input device"). Herein, we propose three algorithms to address this issue.

Algorithm 1 retrieves posts using labels from the same category in the Microsoft COCO dataset and determines hashtags from posts where such labels coexist as hashtags. Algorithm 2 determines hashtags by translating labels into six different languages and retrieving relevant posts. Algorithm 3 is a hybrid of Algorithms 1 and 2.

A questionnaire was administered to 15 subjects to evaluate the proposed algorithms in terms of predicting hashtags for five labels: "spoon," "bear," "mouse," "keyboard," and "train." The average relevance of hashtags predicted for "spoon," "bear," and "mouse" using Algorithm 1 was higher than that of hashtags predicted using the algorithm reported in a previous study. The relevance of hashtags predicted by Algorithm 2 for "train" was high; however, that for "mouse" and "keyboard" was low, which can be attributed to translation ambiguities. Algorithm 3 exhibited no extremely low values for all labels.

Overall, the proposed algorithms predicted hashtags with improved relevance values for different labels. Considering the top 10 and 30 hashtags based on the co-occurrence counts, compared with the algorithm proposed in a previous study, the relevance of the hashtags predicted by Algorithm 1 increased by 59% and 18%, and that for the hashtags predicted by Algorithm 2 increased 45% and 64%, respectively. These results confirm the effectiveness of the proposed algorithms in suggesting hashtags for labels with multiple meanings. In future studies, the accuracy of the hashtag recommendation model using the Human-in-the-Loop method [14] can be improved by considering users' opinions.

**Data availability** The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to their containing information that could compromise the privacy of research participants.

## References


1. Ha, Y., Kim, J., Won, D., Cha, M., & Joo, J. (2018). Characterizing clickbaits on Instagram. In *Proceedings of the AAAI conference on web and social media*, Vol. *12*, No. 1.
2. Chung-Wen, C., Ting-Kuang, Y., Shu-Wen, C., & Chun-Yen, C. (2012). The searching effectiveness of social tagging in museum websites. *Journal of Educational Technology and Society, 15*(4), 126–136.
3. Fedushko, S., & Kolos, S. (2019). Effective strategies for using hashtags in online communication. *International Journal of Computing and Related Technologies, 2*(2), 82–90.
4. Takenaka, H., Komiya, K., & Kotani, Y. (2011). Hashtag classification of tweet in Twitter using Bayesian filterling. *IPSJ SIG Technical Report,* Vol. 2011, No. 1, pp. 1–6 **(in Japanese)**.
5. Zangerle, E., Gassler, W., & Specht, G. (2011). Recommending#-tags in Twitter. In *Proceedings of the workshop on semantic adaptive social web (SASWeb 2011)*, Vol. 730.
6. Godin, F., Slavkovikj, V., De Neve, W., Schrauwen, B., & Van de Walle, R. (2013). Using topic models for Twitter hashtag recommendation. In *Proceedings of the 22nd international conference on world wide web*, pp. 593–596.
7. Mon Kywe, S., Hoang, T., Lim, E., & Zhu, F. (2012). On recommending hashtags in Twitter networks. In *International conference on social informatics* (pp. 337–350). Springer.
8. Zhiyuan, L., Chen, X., & Sun, M. (2011). A simple word trigger method for social tag suggestion. In *Proceedings of the 2011 conference on empirical methods in natural language processing*.
9. Zhuoye, D., Xipeng, Q., Qi, Z., & Xuanjing, H. (2013). Learning topical translation model for microblog hashtag suggestion. In *Twenty-third international joint conference on artificial intelligence*.
10. Kamino, E., & Kita, E. (2022). Prediction algorithm of hashtags for image posting social network services. *Review of Socionetwork Strategies, 16*(2), 291–305.
11. Elke, E., Frissen, T., & D'Haenens, L. (2019). From #selfie to #edgy. Hashtag networks and images associated with the hashtag #jews on Instagram. *Telematics and Informatics, 44*, 101275.
12. Redmon, J., Divvala, S., Girshick, R., & Farhadi, A. (2016). You only look once: Unified, real-time object detection. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 779–788.
13. Lin, T., Maire, M., Belongie, S., Bourdev, L., Girshick, R., Hays, J., Perona, P., Ramanan, D., Lawrence Zitnick, C., & Dollár, P. (2014). Microsoft coco: Common objects in context. In *European conference on computer vision* (pp. 740–755). Springer.
14. Kamino, E., Onose, R., & Kita, E. (2020). Examination of tag recommendation method using human-in-the-loop for enhancing the visibility of SNS post images. *IPSJ SIG Technical Report*, Vol. 2020-MPS-130, No. 3 **(in Japanese)**.