Ethical Practices for Collecting Ground-Truth Food Datasets: A Systematic Review

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***Abstract*— Food image dataset collection for artificial intelligence (AI) studies has ethical concerns that are underestimated. Thousands and millions of images are collected from different sources on the Web, with ethical challenges relating to copyright. While it is difficult to collect large amounts of food images based on permissions, a small number of datasets can affect the performance of the machine learning model (MLM). It becomes imperative to consider a balance between ethics, data collection, and machine learning model performance. We present state-of-the-art ethical considerations for collecting food image datasets. A total of 102 papers were reviewed, and we found that only a few papers (4) reported on the ethical practices they adopted for collecting food image datasets. These ethical practices include obtaining permissions from data sources such as websites and social media sites and obtaining ethical approval for collecting food datasets from participants in food logging studies. For future work, we present opportunities, challenges, and recommendations for considering dataset collection in the food domain. Though there are challenges around collecting datasets that are sufficient for training MLMs, we provide recommendations to balance the trade-off between gathering large datasets ethically and improving the accuracy of MLMs.**

Keywords—food, datasets, images, machine learning models, ethics, AI

I. Introduction

The use of large datasets, including those containing images of food, is common in training machine learning models (MLMs). Most of these images are copyright protected, others are free to use and adapt. However, ethical considerations surrounding Artificial Intelligence (AI) datasets are increasingly recognized as a critical aspect of responsible AI development [109]. Data privacy and consent, copyright, fairness, transparency and accountability are some of the major ethical challenges arising in the area of food image recognition [111]. For instance, unauthorized use of copyrighted material may lead to legal consequences. The training data may not be representative, leading to biased models that perform poorly on certain types of food or in specific cultural contexts. Additionally, lack of transparency regarding the sources and composition of training datasets can hinder accountability and trust in AI systems [114, 115].

Addressing these ethical challenges requires a holistic approach that involves collaboration between researchers, developers, and the wider community [110]. Which will also emphasize the importance of ongoing ethical scrutiny throughout the entire lifecycle of the machine learning model, from data collection to deployment. For example, Boyd [2] reported on ethical challenges with training data collected for machine learning studies. In the study, they identified ethical violations such as privacy, fairness, and accountability.

Food image recognition has been the subject of many studies, and a lot of progress has been made in creating ground-truth datasets [42, 112, 113]. However, the issue of training MLM without following proper ethical guidelines is a topic that needs to be addressed. In this systematic review, we aim to expand on this topic by focusing on food recognition systems that rely on data collected from various sources. Our goal is to provide the research community with insights into the ethical challenges involved in collecting ground-truth datasets and explore how ethical standards can be applied to these systems in training machine learning models. Hence, the following are the contributions of this paper:

- Presenting different sources, study locations, and data extraction techniques for collecting ground-truth food datasets.
- Presenting ethical considerations for collecting ground-truth food datasets.
- Comparing recent ethical considerations from a related food data collection study [1].

The rest of this paper is structured as follows: Section 2 presents the methodology (PRISMA) employed in selecting related papers for the review. Section 3 provides significant insights from related papers reviewed, such as the different sources of food dataset collection, study locations where ground-truth datasets were reported, data extraction techniques, and ethical practices. Section 4 covers discussion on ethical practices and overlapping concepts from the different sources of food datasets and data extraction techniques. In addition, Section 4 provides significant insights on providing a balance between ethical practices, the problem of sufficient datasets, and machine learning model accuracy. Section 5 presents a conclusion based on insights drawn from the review. Also, Section 5 covers recommendations for future work on food dataset collection.

II. Methodology

We conducted a thorough review of three widely used electronic databases, namely the ACM (Association for Computing Machinery) Digital Library, IEEE (Institute of Electrical and Electronics Engineers) Xplore and ScienceDirect. The ACM Digital Library is a massive database covering interdisciplinary areas, primarily related to computer science. The IEEE Xplore database contains articles on computing and electrical electronics, while the

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ScienceDirect database is home to articles on computing, medical, and scientific research. Although we obtained 419 search results from the ScienceDirect database, none of them were relevant to our paper. Therefore, we did not consider these results in our paper selection process. Instead, we focused our data collection on the ACM and IEEE databases, from where we gathered a total of 1,516 peer-reviewed papers published in the last five years (between January 2019 and November 2023) from conference proceedings and journals. The search was conducted on November 30, 2023. To ensure transparency, we followed the PRISMA guidelines in reporting our paper selection process, as depicted in Fig. 1.

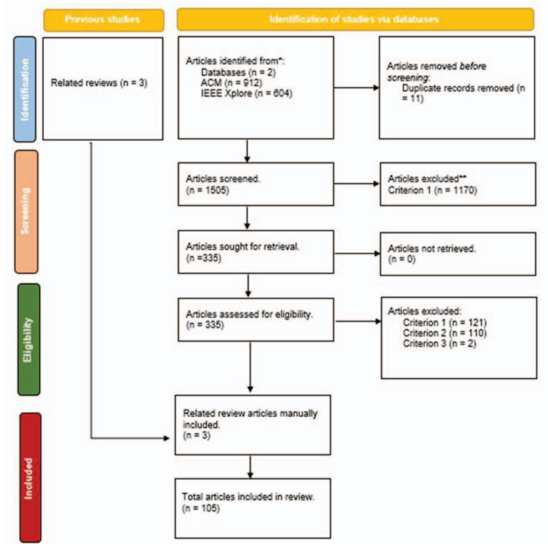

Fig. 1. PRISMA showing review article filtering procedure

A. Paper Identification

We conducted our search by using specific keywords and logical operators (AND/OR) to look for abstracts, titles, and metadata related to food image recognition. This search was performed on three electronic databases, and a total of 1,935 papers were collected. The authors screened all the collected papers and found that out of the 419 ScienceDirect articles, none were relevant to our review. These articles were removed, leaving us with 1,516 papers from ACM (912) and IEEE (604).

B. Paper Selection

We began with a set of 1,516 papers. After removing 11 duplicates, we screened out 1,170 papers based on their title. Then, we manually evaluated the remaining papers to determine if they met our inclusion and exclusion criteria. Our inclusion criteria cover the following:

Our inclusion criteria cover the following:

- Papers should report on ground-truth food dataset collection.
- The papers should cover food recognition-related studies.
- The paper should be written in English.

Based on this inclusion criteria, 121 papers did not meet our first criterion, while 110 papers failed to meet our second criterion. Additionally, two papers were not in English, which failed our third criterion. As a result, we excluded a total of 233 papers, and included 102 papers in our review. Furthermore, we gathered three review articles manually for the related work section.

C. Information Extraction

We carefully examined the complete texts of the chosen papers and gathered information according to various categories of findings (listed below). Three researchers collaborated to code this information in a coding worksheet. In this report, we provide insights based on the information we gathered in the following categories:

- The different sources for collecting ground-truth food datasets.
- The different study locations where ground-truth food datasets were collected and reported.
- Data extraction techniques for a ground-truth food dataset.
- Ethical practices for collecting food datasets from different sources for AI research.

1. **Different ground-truth food data sources:** We have identified various sources of ground-truth data for each article, such as the web, the field (restaurants), social media, experiments (food logging apps), and other significant ones. Moreover, we have elaborated on specific food data sources from the web, field, and social media. Some examples of these sources include Google images, restaurants, and Facebook.

2. **Different study locations for ground-truth food dataset collection:** We identified the various locations where reliable food datasets were reported in the articles we reviewed. Our analysis revealed how food items have been recorded in different countries across the world, including China, Indonesia, the USA, and other important nations.

3. **Data extraction techniques for the ground-truth food dataset:** We reviewed articles using various methodological approaches, including crawling, logging, downloading, clipping, camera capture, and other related ones.

4. **Ethical practices:** We identified various ethical practices in the articles we reviewed. This included seeking permission from food vendors or web pages. Additionally, we coded articles where this information was not explicitly stated as N/A or not stated (N/S).

III. RESULTS

From the articles we reviewed, we found that food dataset collection durations ranged from 3 days to 8 years. On average, 60,685 datasets were collected from various sources.

A. Demographics of Paper Reviewed

Out of the 102 papers reviewed, 88 were conference publications and 14 were journal papers. The majority of these articles were published between 2020 and 2022 (Fig. 2).

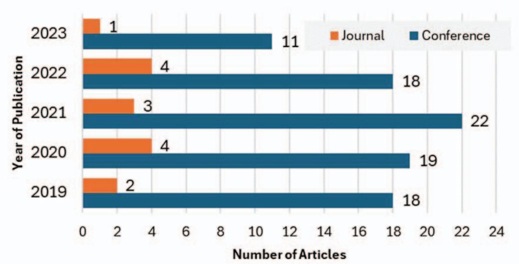

Fig. 2. Distribution of Articles by Year of Publication.

B. *Representation of ground-Truth food data collection by location*

According to our review of various articles, ground-truth food dataset has been collected for 27 countries. The distribution of the number of articles is presented in Figure 3. The majority of the reviewed articles indicate that China (26.47%) has conducted the most studies on ground-truth food dataset collection [17-42, 78]. However, India (10.78%) [48-58], Indonesia (8.82%) [59-67], and Japan (7.84%) [69-76] have also conducted significant studies. Nonetheless, other countries' foods require further studies in the future.

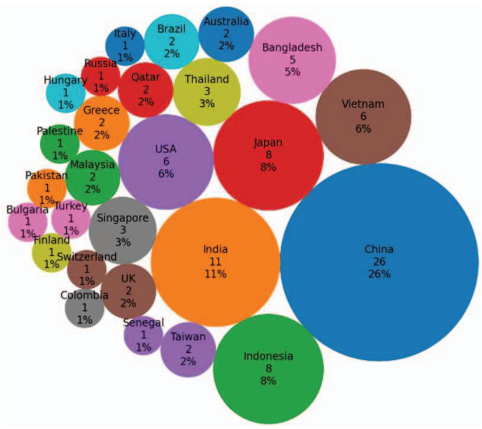

Fig. 3. Distribution of Articles Reviewed by Country.

C. *Different ground-Truth food data sources*

We found different sources where ground-truth food datasets were collected from the web, field, social media, others and food logging App (Fig. 4). There more instances (66) of data collected from the web (Fig. 5). Out of the 66 instances, 18 articles referenced Google images [11, 13, 14, 19, 21, 31, 38, 60, 68, 78, 81, 82, 84, 86, 92, 93, 104, 105]. Fifteen (15) articles did not specify a web source [10, 39, 40, 45, 46, 47, 48, 49, 56, 62, 75, 77, 89, 106, 107]. Fifteen (15) articles primarily used food websites, while 8 articles referred to Flickr and another 8 articles used Bing. Additionally, one article collected data from Wikipedia, and another one made use of Pinterest. We also found that 34 instances of field data collection took place, with different categories mentioned in Fig. 6. Specifically, 18 articles did not specify a field source, 7 articles collected data from home settings, 6 from market spaces, two (2) from restaurants, and one (1) from an underwater source. Furthermore, we observed that 15 instances of social media data sources were used, with different categories mentioned in Fig. 7. Seven articles employed Instagram, while four (4) used Facebook. Two articles employed Twitter, while one (1) article used Weibo, and another one did not mention the type of social media used.

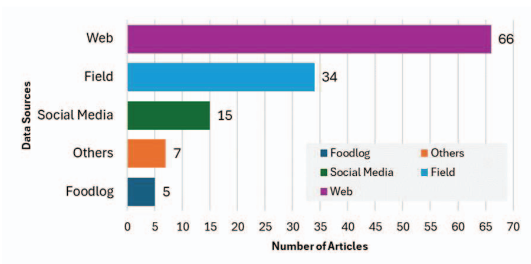

Fig. 4. Sources of Data Collection.

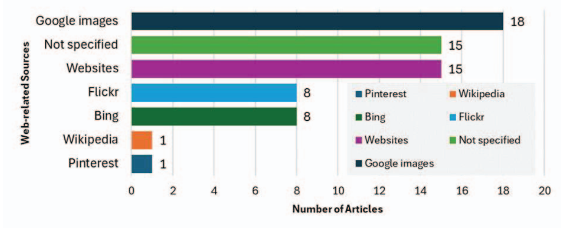

Fig. 5. Web-related data source.

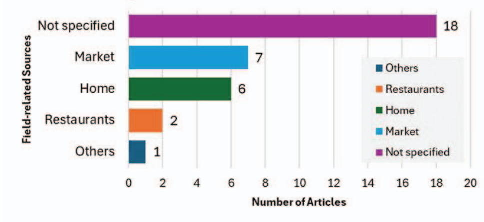

Fig. 6. Field-related data sources.

D. *Data extraction techniques for ground-truth food dataset*

We came across 102 articles that explored various data extraction techniques (Fig. 8). Out of these, 36 articles focus on the use of cameras [8, 9, 12, 15, 16, 23, 25, 28, 29, 32, 34, 35, 40, 43, 44, 45, 50, 57, 59, 63, 64, 66, 67, 70, 71, 74, 80, 84, 85, 89, 91, 94, 95, 96, 98, 100] while 30 articles employed crawling and downloading data techniques [18, 19, 20, 21, 24, 27, 31, 38, 42, 47, 48, 60, 61, 62, 68, 72, 76, 77, 78, 79, 81, 82, 83, 86, 87, 92, 97, 102, 105, 108]. The data extraction techniques in 23 articles were not specified [10, 13, 17, 36, 37, 39, 46, 49, 51, 52, 53, 54, 55, 56, 58, 65, 73, 90, 93, 103, 104, 106, 107]. Four (4) articles focus on other forms of data extraction, such as using image capture script [14], CIGM tool [22], text descriptions [33], and food brands [41]. Three (3) instances reported on algorithm-based data extraction [26, 69, 75], and three (3) instances of food logging were reported in the reviewed articles [7, 88, 99]. Two (2) articles reported re-annotation [30, 101], and one (1) article discussed data augmentation for extracting food images from existing food datasets [11].

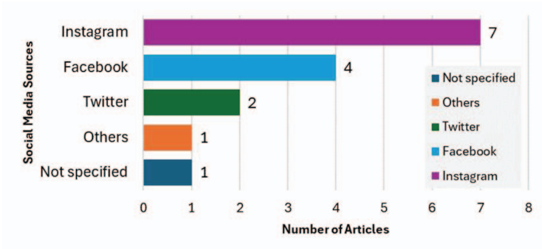

Fig. 7. Social media-related data sources.

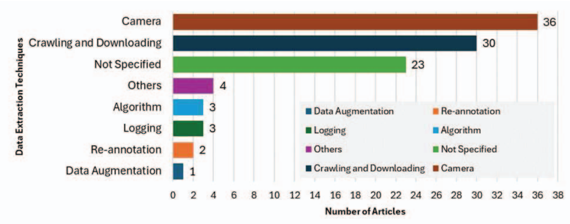

Fig. 8. Data extraction techniques.

E. *Ethical considerations and Issues*

Overall, we found three (3) ethical issues associated with ground-truth food dataset collection. These include 1) issues with consent seeking and respect for autonomy, 2) privacy concerns, and 3) issues with fairness (bias) in models developed based on ground-truth datasets. Consent seeking and respect for autonomy ensures that owners of data are informed of who is having access to their data and how their data will be used [115]. Privacy respects boundaries between personal data and its' use [115]. Fairness ensures that there is no bias in data collected or decisions made with such data [115].

1. **Issues with consent seeking and respect for autonomy:** We found that out of 102 articles reviewed, only 4 (4%) of them considered consent seeking and respect for autonomy [7, 21, 88, 98]. One of the studies, conducted by Jung et al. [7], involved a large-scale nutrition study using a food-logging app (Eat) with 1,027 participants. In order to engage participants, ethical approval was obtained to recruit them for the experiment. Another study, conducted by Min et al. [21], obtained permissions from an online restaurant called "Meituan" and collected 1,036,564 food datasets (called Food2K). Hossain et al. [98] also obtained ethical approval to collect food datasets (3,192) by monitoring participants' food intake in real-time. Lastly, Gligoric et al. [88] contacted volunteer users of a food logging app (MyFoodRepo) for a duration of 4 years (2017–2020) and collected a total of 24,120 food datasets. Typically, ethical approval addresses consent seeking and respect for autonomy. Hence, the percentage covering this aspect for consent seeking and respect for autonomy from this study (3%) is relatively low.
2. **Privacy concerns:** Also, while studies with ethical approval also addresses privacy concerns where personal data is collected, we found one instance that involve a classification of food and non-food related items [98]. In view of this, users are to log food and non-food items in real time. This implies that the users could upload privacy-related items.
3. **Issues with fairness (bias):** Another ethical challenge we found from the papers we reviewed was some kind of bias especially in instances where diverse data were collected, most models were biased to certain foods compared to others [8, 9, 10, 12, 13, 14, 15, 32, 34, 47, 50, 52, 53, 54, 57, 60, 62, 66, 68, 71, 72, 77, 81, 85, 86, 90, 91, 94, 95, 96, 98, 99, 105, 106, 107]. For example, Mao et al [8] trained a VGG11 model to predict 16 classes of foods (Apple, apple juice, beef, bottle of milk, bread, broccoli, butter, carrot, custard, jelly, mashed potato, meatball, pear juice, potato, sandwich, and soup). However, the model performed well on foods such as bottle of milk, broccoli, custard, meatball, and pear juice compared to other foods. In other cases, the performance of the model across these foods is not provided to understand the transparency of this model [18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 33, 37, 40, 41, 42, 44, 45, 46, 48, 49, 51, 55, 56, 58, 59, 61, 63, 64, 65, 67, 70, 73, 74, 75, 76, 78, 80, 82, 84, 92, 93, 97, 100, 101, 102, 103, 104, 108]. For example, Min et al. [21] developed an SGLANet model for classifying western and eastern foods. The overall performance of the model was reported to be 90.98%, however, the performance of this model on the individual western and eastern foods was not evaluated. This becomes important to review these Apps in future to enhance fairness. Research has shown that due to bias in AI systems, people do not trust them [115]. Though machine learning models cannot completely eliminate bias, it should be minimal. For example, we found instances where there was a slight difference in the performance of the model on one class of food compared to others [11, 38, 39]. For example, Nguyen et al. [38] explored different classes of foods such as Western, Chinese, and Japanese food. In view of this, they trained a SibNet model and evaluated the performance of individual classes. Results from this study revealed that the western food (cookie) attained an accuracy of 89.83%, the Chinese food (Dimsum) attained an accuracy of 88.99% and Japanese food (Sushi) attained an accuracy of 86.53%.

IV. DISCUSSION

The study reveals a large number of research projects carried out in the field of food image recognition. However, given the vast amount of work that still needs to be done regarding study location and the data sources used, we present our discussion on the ethical challenges associated with these sources. In addition, we present discussions on ways to deal with ethical challenges emerging from these sources. In view of this, we present our discussions under two (2) categories: 1) Ethical challenges and 2) Recommendations for addressing ethical challenges.

A. *Ethical challenges*

Results from our study show the different sources for collecting ground-truth datasets and ethical challenges including consent, respect for privacy, addressing fairness and autonomy. First, we found ground-truth data collection linked to privacy challenges especially where foods are logged. For example, Hossain et al. [98] reported this privacy challenge during the food logging data collection, they found that non-food images might contain private images.

Second, it is important to note that images from some of the food sources we found from our review are copyright protected based on a related work of Ataguba et al. [1]. However, most studies did not cover consent seeking prior to data collection. Conversely, we found an instance where Min et al. [21] collected creative common license food images from Wikipedia. Creative common license images are ethical because these images have been consented to be in the public domain for attribution to creators[1].

Third, we found some kind of bias especially for instances where diverse data were collected, most models were biased to certain foods compared to others. This becomes important to review these Apps in future to enhance fairness. Research has shown that due to bias in AI systems, people do not trust them [114]. Though machine learning models cannot eliminate bias, it should be minimal as reported in few studies [11, 38, 39].

B. *Recommendations*

While it has become important to adhere to ethical practices for ground-truth food data collection, we discuss the recommendations as follows:

1. Inform food page owners on the web and engage them in participatory designs to help them understand the extent to

[1] https://creativecommons.org/

which their data is used. The need to inform and engage food dataset owners in nutrition-related research has been emphasized in literature over the years [114]. This will cater respect for autonomy on the use of data collected. Alternatively, researchers should consider using creative common license image sources such as Wikimedia, Wikipedia, YouTube videos filtered under the creative common license and saving relevant images using relevant image capturing tools [1], and Google image search limited to creative common license.

2. While it might be quite challenging to collect a large number of data through consent to enhance the performance of machine learning models, we recommend that the research community provide a balance by following ethical procedure in dataset collection and considering the use of pre-trained models with data collected ethically (even though they can be small). Pre-trained models have been evaluated on millions of datasets [4] and have shown a significant performance in the development of food recognition models [52, 54, 58, 62, 64, 65, 77]. Additionally, it will be interesting to explore data augmentation techniques with ethically collected datasets to enhance the performance of food recognition models. Data augmentation techniques are useful for increasing the size of datasets by creating new image datasets through rotations, translations, rescaling, flipping, cropping, and color transformation [56]. This was employed with food data collected ethically to enhance the performance of food recognition models in some papers we reviewed [10, 56, 89, 94].

3. To prevent bias in food recognition models as a result of data collected, especially where intercultural or diverse foods are considered, it is essential to consider balancing the datasets. We found instances from papers we reviewed where the performance of the food recognition model across the foods collected was considerable [11, 38, 39]. We recommend that after seeking appropriate consent from food image owners or using ethical sources as creative common license, it is essential to balance the food data or fine tune the model to reduce the bias on its prediction on individual foods.

4. In cases where food logging is employed to collect food images which might raise privacy concerns, extra effort should be put in place to anonymize non-food related images.

V. CONCLUSION

A systematic review was conducted to investigate the various ethical practices used for obtaining ground-truth food datasets. The study analyzed 102 journal articles and conference papers sourced from ACM and IEEE to report on the latest trends in this field. The articles covered different locations for studying ground-truth food datasets, sources for collecting data, and techniques for data collection. The paper provides important insights as follows:

- The need to follow ethical procedure for nutrition-based research has attracted the attention of the research community.
- There are ethical challenges with seeking permission and consent of food page owners, and respect for autonomy while collecting ground-truth food datasets.
- We recommend that future work combines ethically collected data with pretrained models or augmentation techniques to enhance the performance of food recognition models to cater to the three (3) ethical principles: 1) fairness, 2) accountability, and 3) transparency.
- Also, we found bias in how well models predict some classes of foods compared to others. While bias is completely unavoidable, it would be good to set a threshold for which this bias can be minimal (for example, 0.1% cross classes). This is significant considering the dietary and health implications of foods.

Hence, following from these insights, the nutrition-based research community can benefit from ethical design of food recognition systems especially for regions that are yet to be explored as we found from our review.

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