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Deep Learning in Barcode Recognition: A Systematic Literature Review

RATAPOL WUDHIKARN[1,2], PHASIT CHAROENKWAN[2,3], AND KANOKWAN MALANG[3,4]

[1]Department of Knowledge and Innovation Management, College of Arts, Media and Technology, Chiang Mai University, Chiang Mai 50200, Thailand
[2]Research Group of Modern Management and Information Technology, College of Arts, Media and Technology, Chiang Mai University, Chiang Mai 50200, Thailand
[3]Department of Modern Management and Information Technology, College of Arts, Media and Technology, Chiang Mai University, Chiang Mai 50200, Thailand
[4]China Intelligence Center, College of Arts, Media and Technology, Chiang Mai University, Muang, Chiang Mai 50200, Thailand

Corresponding author: Kanokwan Malang (kanokwan.malang@yahoo.com)

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ABSTRACT The use of deep learning (DL) for barcode recognition and analysis has achieved remarkable success and has attracted great attention in various domains. Unlike other barcode recognition methods, DL-based approaches can significantly improve the speed and accuracy of both barcode detection and decoding. However, after almost a decade of progress, the current status of DL-based barcode recognition has yet to be thoroughly explored. Specifically, summaries of key insights and gaps remain unavailable in the literature. Therefore, this study aims to comprehensively review recent applications of DL methods in barcode recognition. We mainly conducted a well-constructed systematic literature review (SLR) approach to collect relevant articles and evaluate and summarize the state of the art. This study's contributions are threefold. First, the paper highlights new DL approaches' applicability to barcode localization and decoding processes and their potential to either reduce the time required or provide higher quality. Second, another main finding of this study signifies an increasing demand for public and specific barcode datasets that allow DL methods to learn more efficiently in the big data era. Finally, we conclude with a discussion on the crucial challenges of DL with respect to barcode recognition, incorporating promising directions for future research development.

INDEX TERMS Barcode, barcode recognition, barcode detection, barcode localization, deep learning, literature review.

I. INTRODUCTION

Barcodes are currently the most widely applied technology used to automatically convey information about packages and objects [1]. Barcode recognition and analysis has attracted considerable attention in both the academic and commercial domains. Barcodes are accepted as the backbone of supply chain management (SCM) owing to their significant advantages (i.e., high reliability and low cost) [2]. Although this established technology was first proposed more than seven decades ago, the barcode is still actively and widely used today. One of the main reasons for this is that newer and more efficient technologies for identifying and tracking objects, such as radio frequency identification (RFID), tend to be more complex and entail higher investment and operational costs [2], [3]. Accordingly, the barcode is likely to remain in use for the foreseeable future [4], [5].

Barcodes offer a means of visualizing data in an encrypted form. Traditional one-dimensional (1D) barcodes represent data in the widths and spacing of parallel lines. Although linear barcodes offer several advantages, they nonetheless have some underlying and critical disadvantages, such as the ability to store only small amounts of data and vital encoding issues associated with barcode damage and distortion. To address these shortcomings, two-dimensional (2D) barcodes were proposed. 2D barcodes offer an improved form of barcode known as matrix codes, which are represented in various forms (i.e., rectangles, dots, hexagons, and other geometric patterns). The distinctive patterns of 2D barcodes allow them to store data on both vertical and horizontal axes, offering greater data storage capacity than that of 1D barcodes [6].

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Both 1D and 2D barcodes require electronic devices to read and extract their information. Several barcode technologies can be applied to read barcodes depending on the barcode type, barcode reader, and the environment in which the decoding is taking place. Key barcode technologies include pen-type readers, laser scanners, charge-coupled device (CCD) scanners, camera-based readers, omnidirectional barcode scanners, and smartphones. Traditional human-operated or handheld barcode readers, such as pen-type readers, laser scanners, and CCD scanners, typically have high reading reliability. However, they retain several critical limitations, including the inability to scan 2D barcodes, the inability to read several 1D barcodes simultaneously, and poor reliability when scanning barcodes from screens or monitors. The extent of these issues and technological advancements (i.e., computer vision-based or image processing-based barcode reading) have caused automatic barcode identification and barcode analysis to attract significant attention in recent years [7].

When computer vision (CV) applications for barcode recognition were first introduced, conventional image processing approaches were widely adopted [8]. However, these methods involve manual work, making them more complex and inefficient, particularly when dealing with massive amounts of data [7]. Therefore, several studies on barcode recognition have applied deep learning (DL) methods in the past few years. Unlike conventional methods, DL's recent progress and distinctive advantages have been revealed as significant and capable of improving the speed and accuracy of barcode detection. With respect to image recognition, DL applications have recently been exponentially investigated across several fields and topics. In light of DL's broad and various applications in the past, the results may highlight their advantages, disadvantages, challenges, and limitations in several situations. To obtain a more comprehensive assessment, findings from various studies should be collected and analyzed as a means of appraising current situations, strengths, weaknesses, improvement opportunities, and even reasons for caution with respect to DL applications through the literature review study.

Several survey studies published in the last decade explored the successes, advancements, and limitations of DL applications in various fields. These studies aimed to investigate and conclude significant findings across several dimensions to create value for both academics and practitioners. However, most review studies hitherto focusing on DL and CV have been limited to specific end user groups, particularly in the medical domain. Studies focusing on domains or situations relating to daily life or manufacturing industries remain limited, despite the likely significant advantages of applying DL to CV to humans and industries.

Moreover, one type of DL method—convolutional neural networks (CNNs), also known as deep-CNNs (D-CNNs) [9]—is identified as the most significant DL method for CV. This method could improve the speed and reduce the complexity of model creation and data analysis processes in several CV tasks [10]. Nowadays, D-CNNs are widely trusted and applied in various studies/domains. They are also likely to become the most widely accepted and applied DL method in CV-related tasks in the future [11]. Similar to the above-mentioned review studies of DL in CV, the number of literature review studies of D-CNNs and CV in topics relating to daily life or manufacturing tasks (e.g., barcode detection) is also limited. Only four related review articles examined different topics or scopes, including retail product recognition [12], material degradation analysis [13], collision avoidance for unmanned aerial vehicles (UAV) [14], and plant disease detection [11].

Hitherto, no study has surveyed and reviewed the application of D-CNNs in barcode analysis exclusively, despite the known successes that this advanced technology adoption has shown in supporting human daily life activities. Moreover, D-CNN allows the manufacturing industry to improve the quality of barcode images and analyze barcodes with greater precision at real-time speed [15]–[17]. In recognition of the gap in existing review research, the significant increment of popularity as well as the potential applications of D-CNN-based barcode recognition, and advantages and knowledge obtained from the literature review, this study aims to perform a comprehensive survey of studies relating to the application of D-CNNs in barcode recognition. The findings obtained will reveal the existing achievements, limitations, current progress, and improvement opportunities in this research field, and these will benefit both academics and practitioners. These outputs will support practitioners in selecting proper D-CNN methods corresponding to the barcode recognition situations and handling all possible challenges and limitations. At the same time, the study will provide an overview of the current progress and status of D-CNN-based barcode recognition topics for academics. This will allow them to negotiate opportunities for improvement and fill the knowledge gaps in this area. This paper largely followed the proven systematic literature review (SLR) approach [18] to comprehensively and systematically review related studies.

The remainder of this paper is organized as follows: In the next section, the scope and theoretical concepts of the methods related to this study are detailed. Section 3 describes the review methodology used in this study. Section 4 provides the descriptive results and findings with respect to the research questions and analyzes the results. Finally, Section 5 concludes the paper and highlights the significant challenges associated with the topic and the study's limitations. In the interest of readability, all acronyms employed throughout this paper are listed in Table 1. The page numbers on which each acronym is first identified are also given.

II. A COMPUTER VISION METHOD IN BARCODE RECOGNITION

A. CONVENTIONAL METHODS

Amid the advancement and distinctive advantages of CV technology in recent decades, dynamic new methods for

TABLE 1. List of acronyms used in the paper.

Acronym	Definition	Page no.
1D	one-dimensional	1
2D	two-dimensional	1
ANN	artificial neural network	3
CCD	charge-coupled device	2
CNNs	convolutional neural networks	2
CV	computer vision	2
D-CNNs	deep convolutional neural networks	2
DL	deep learning	2
DSC	depth-wise separable convolution	10
IoT	Internet of Things	3
ML	machine learning	3
MLP	multi-layer perceptron	4
PR	public relation	13
R-CNN	region-based convolutional neural network	4
RFID	radio frequency identification	1
RQs	research questions	5
SCM	supply chain management	1
scRNA-seq	single-cell RNA sequencing	3
SLR	systematic literature review	2
SSD	single shot detector	4
UAV	unmanned aerial vehicle	2
WoS	Web of Science	6
YOLO	You-Only-Look-Once	4

detecting and decoding barcodes have been proposed. Barcode recognition, which relies on the CV concept, can generally be divided into two major tasks: barcode locating and decoding. To achieve these goals, barcode recognition systems include five major components: (1) image acquisition: a digital image is produced and collected from an electronic device, such as digital camera, smartphone, and scanner; (2) image preprocessing and segmentation: this function aims to improve the quality of the image to increase the accuracy of image analysis in subsequent processes. Various approaches to image preprocessing have been proposed, such as image denoising [19], image resolution enhancement [20], and image quality improvement [21], [22]. In this stage, a focused region is segmented from the background and subsequently processed by rotation, translation, scaling, or contrast normalization technique; (3) feature extraction: this component's key purpose is to reduce the original image dimension or data set by removing unreliable, redundant, and unnecessary components from the image or data. In this stage, several methods, techniques, and algorithms can be applied to extract the features of a digitized image; (4) feature classification: to accurately recognize an image or barcode, the feature classification process applies a specific decision rule to classify a low-dimensional image object obtained from the previous stage; (5) post-processing: an extracted and classified object is analyzed for the required information. In the barcode recognition system, the obtained image or barcode is further decoded using an appropriate algorithm.

Although CV methods significantly benefit barcode recognition, they continue to present several challenges and disadvantages. Given the existence of numerous classes and features, the optimal features for classifying various visual objects must be manually selected. Several parameters also require manual configuration according to each feature [23]. Moreover, the operation requires advanced engineering skills and must be executed by an expert in the field, leading to a lengthy trial-and-error process [24]. Regarding the manual elements of traditional CV methods, several recent attempts have sought to improve the above-mentioned limitations of barcode recognition. DL is one of the dominant methods and core solutions that have been widely adapted on the basis of their successful application to barcode location and decoding.

B. DEEP LEARNING (DL) AND CONVOLUTIONAL NEURAL NETWORKS (CNNs)

Over the last decade, DL has come to be known as deep structured learning. It can significantly surpass human ability, efficiently resolve various real-life problems, and present the great promise as a practical solution in several domains or situations such as computer games [25], communication system [26], mobile traffic classification [27], IoT-based UAV systems [14], named entity recognition [28], as well as the most recent research in biological domain that points out at the potential of DL in scRNA-seq data analysis [29].

To accomplish complex tasks in the CV domain, DL is widely applied in image classification, segmentation, and recognition [30]. Although this technique is considered a subfield of machine learning (ML), it structures and uses artificial neural networks (ANNs) differently to enable machines to make accurate decisions without relying on human supervision. Among DL's key features is its ability to represent and classify data simultaneously, thus constituting a significant improvement on conventional ML techniques. Unlike other conventional techniques, DL supports engineers in optimally performing several tasks such as feature extraction, feature classification, semantic segmentation, and object detection over the traditional signals (i.e., image, sound, video or text). Rather than that the practical applications of DL technologies, especially CNNs have been proved to be useful for analyzing data in a form of graph and manifold, namely geometric DL [31]. These distinctive advantages, as well as the rapid progression of DL alongside technological advancements (i.e., computing power and visual performance, devices' image resolution, and the improved cost- effectiveness of both hardware and software) [12], [30], have accelerated the application of DL across several domains, such as medical, SCM, and manufacturing industries.

Barcode recognition is among the research fields that have applied DL-based approaches and obtained several significant advantages over the traditional methods. A review of several studies revealed that only two major DL methods were applied—the multi-layer perceptron (MLP) and CNNs or D-CNNs. Of these two major techniques, D-CNNs are among the most popular and commonly utilized DL algorithms [32]. It represents the distinctive evolution of ANN and MLP architectures, which can effectively and efficiently analyze images. One of D-CNNs' main capabilities is resolving the problem of information loss associated with the transformation of 2D images to 1D vectors. This loss of information is typically found in traditional ANNs or MLPs [10].

Regarding the distinctive advantages of D-CNNs, they are now broadly recognized as the most widely applied DL networks [33], [34] and have been adopted for use in the CV domain [35]. Several D-CNN architectures have been developed continuously for CV tasks, such as region-based CNN (R-CNN), Fast R-CNN, Faster R-CNN, single shot detector (SSD), and you-only-look-once (YOLO) approaches. Interestingly, the adoption of DL, particularly D-CNN architectures in barcode analysis, has significantly increased in the CV community in recent years. Moreover, past studies' findings have indicated that D-CNN's applications in barcode recognition could assist humans in precisely, accurately, and instantly detecting and decoding barcodes. It is also better able to deal with barcode recognition issues, such as blurring and distortion, than other DL techniques [36], [37]. D-CNN's abilities and advantages in barcode recognition harmonize with the requirements of real-life applications for both commercial and public sector. Therefore, in view of its significant impacts, several studies have applied D-CNN to utilize its distinctive abilities for improving risks and issues associated with barcode recognition.

Current definitions of DL are broad and inconsistent, and various architectures have been assigned to the DL category. It is thus necessary to clarify DL's scope as it relates to this study. Accordingly, only D-CNN architectures are considered in the literature review. This decision is based on D-CNN's significant advantages and considerable success in CV and barcode recognition, as mentioned above. Studies of barcode recognition can be broadly classified into three categories: localizing, decoding, and both localizing and decoding.

From these DL-based barcode recognition tasks, past studies have used several common performance measures. The definition and principal performance of the key evaluation metrics for assessing the accuracy and effectiveness of barcode recognition and analysis are given as follows:

The first standard evaluation metric for object detection is the precision rate (P_t). P_t measures how close the barcode detection's results are to the observed value. It can be calculated by (1).

$$P_t = \frac{TP}{TP + FP} \tag{1}$$

where TP is true positive, or the number of barcodes correctly recognized by the DL model. $TP + FP$ is true positive and false positive, representing the actual number of all barcodes that the model can recognize.

Accuracy rate (A_t) describes the DL model's performance across all classes of barcode detection results. A_t is defined as follows:

$$A_t = \frac{TP + TN}{TP + TN + FP + FN} \tag{2}$$

where $TP + TN$ is the number of correct predictions (the number of barcodes that the DL model classified correctly, both true and false) to the total number of barcode samples.

Recall rate (R_t) also known as sensitivity. It represents the probability of ground truth barcode images being correctly detected. The definition of R_t denoted in (3).

$$R_t = \frac{TP}{TP + FN} \tag{3}$$

where TP is true positive, or the number of barcodes correctly recognized by the DL model. $TP + FN$ is true positive and false negative representing all possible number of detected barcodes.

Mean average precision (mAP) is commonly used to evaluate the performance of DL methods in object detection tasks. It can be calculated according to the Average Precision (AP) of different classes. Meanwhile, AP is obtained by measuring pairs of precision and recall value for different ranks based on the confidence level [17].

$$AP = \sum\nolimits_n (R_n - R_{n-1}) P_n \tag{4}$$

$$mAP = \frac{1}{N} \sum_n^N AP_n \tag{5}$$

For decoding tasks, the success rate S_t is frequently used to reflect the decoding performance. S_t is one of the simple metrics to measure the validity of the D-CNN based barcode recognition methods. It can be calculated by counting the number of successfully decoded barcodes D against the number of barcode images included in the test set T. The definition of S_t is given in (6). The higher S_t value refers to the D-CNN method's greater decoding ability.

$$S_t = \frac{D}{T} \tag{6}$$

Although, the current application of DL in barcode recognition has attracted considerable attention, interestingly, no single review has summarized its progress, achievements, or associated challenges. To the best of our knowledge, only a limited number of review studies has focused on D-CNNs and their CV-related scope, as presented in Table 2. Each survey emphasized the different fields of study, and, until now, reviews of DL-based barcode recognition have been rare. However, in light of findings reported in relevant studies, all studies presented in Table 2 can illustrate current progress and advancement, and limitations associated with D-CNN's application in different fields. These findings could benefit academics and practitioners in term of improving methods and the proper adoption of methods regarding the situations respectively. Nevertheless, some of the surveys lack any consideration of the analysis of the applied datasets while the others only present perfunctory analyses. We argue that most recent studies on D-CNN have been increasingly less concerned with in-depth analysis of barcode dataset issues (e.g., barcode utilization schemes) and best practices for dataset handling to enhance the model generalization abilities. Existing studies have failed to make valid suggestions for the development and improvement of datasets or resources, which are sorely needed in new research topics relating to DL. These limitations make current studies more difficult to perform barcode analysis and recognition tasks efficiently, particularly with respect to extraordinarily large and complex barcode datasets. Therefore, in recognition for the opportunities to improve data resource analysis in D-CNN-based studies as well as the D-CNN approach's current popularity, potential applications, importance, and limitations with respect to barcode recognition, this study aims to review this topic systematically.

TABLE 2. The related literature review studies.

Authors	Year	Fields	Number of articles[a]
Nash, W., Drummond, T., and Birbilis, N. [13]	2018	Material degradation analysis	27
Fraga-Lamas, P., Ramos, L., Mondéjar-Guerra, V., and Fernández-Caramés, T.M. [14]	2019	UAV systems for autonomous obstacle detection and collision avoidance	12
Wei, Y., Tran, S., Xu, S., Kang, B., and Springer, M. [12]	2020	Retail product recognition	18
Nagaraju1, M., and Chawla, P. [11]	2020	Plant disease detection	18

[a]Number of articles refers to the particular D-CNN papers.

III. MATERIALS AND METHODS

To systematically investigate the current status, progression, and future potential of DL-based barcode analysis applications, the SLR approach [18] was applied in this study. The overall SLR approach applied in past SLR studies reflects a systematic process and yields detailed information, as depicted in Fig. 1.

As Fig. 1 illustrates, the SLR procedure consists of three major phases: planning, conducting, and reporting. Meanwhile, the overall process is divided into seven steps. The complete details and procedures of all stages are explained as follows:

A. ESSENCE OF SYSTEMATIC LITERATURE REVIEW

Several studies published in recent years have specifically applied DL to barcode recognition. However, the existing methodologies, research scope (e.g., type of barcodes and DL methods), and findings were still varied. Without analysis and summarized results from diverse and widely distributed studies, scholars and practitioners cannot fully appreciate DL's current status or past development. Investigations of DL-based barcode recognition that neglect the SLR approach are also limited with respect to observing future DL application trends. In an attempt to address the abovementioned issues and to fully appreciate the development, results, and gaps in this field, the present study systematically reviews DL's application in barcode recognition.

B. IDENTIFICATION OF RESEARCH QUESTIONS (RQs)

To obtain and clearly review all required information from the review process, this study is guided by the following research questions:

RQ1: What types of barcodes and DL (CNN) methods were used in the barcode analysis literature?

RQ2: What datasets were used in the literature?

RQ3: What major findings and challenges or limitations were reported in the literature?

C. FORMATION OF REVIEW PROTOCOL

The protocol used to systematically review the literature is formulated and described in this section to support reproducibility. To identify all potentially relevant studies in the primary search, three broad keywords and their synonyms, acronyms, and related terms as well as search strings were identified prior to use, as Table 3 illustrates.

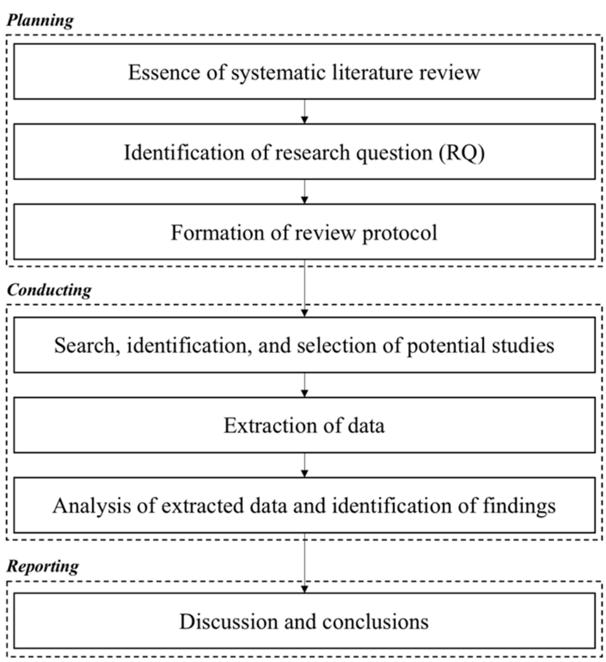

FIGURE 1. The SLR process.

Thence, to execute an inclusive search, the Boolean operators ("AND" and "OR") were applied with the identified keywords shown in Table 3. The "OR" operator was used to connect the main search terms and their synonyms, acronyms, and related terms. Meanwhile, the "AND" operator was applied to concatenate between search terms. Specifically, the search terms used in this study are presented as follows: ("deep learning" OR "DL") AND ("barcode" OR "bar code" OR "QR code") AND ("analysis" OR "detect*" OR "decod*" OR "locali*"). To execute a primary search and maximize the identification of potentially relevant papers, the search period was defined to cover articles published from 2010 to November 2021. In line with this, articles from two well-regarded online research databases—Web of Science (apps.webofknowledge.com) and SCOPUS (www.scopus.com)—were also considered.

TABLE 3. The search terms, synonyms, and search strings.

Main search term	Synonym, acronym, and related term	Description
deep learning	DL	The direct term ("deep learning") and acronym ("DL") are applied to cover the whole studies related to deep learning.
barcode	bar code, QR code	The search term, which is "barcode," and direct related terms ("bar code" and "QR code") are applied to search an article that is all possibly relevant to a barcode-related study.
analysis	detect*, decod*, locali*	To detect the analysis of barcode from searched studies, the direct and broad keyword, which is "analysis", is applied. For synonyms as well as other related terms searched, the "detecti*" is used to cover detect, detection, and detecting, the "decod*" covers decoding and decode, and finally the "locali*" is adopted to cover localize, localization, localise, and localisation.

D. SEARCH, IDENTIFICATION, AND SELECTION OF POTENTIAL STUDIES

In this step, irrelevant and unqualified studies identified by the extensive searching approach of the previous step were filtered. The exclusion criteria are identified as follows: articles not written in English, articles that are not classified in the domains of "computer science," "engineering," "social sciences," "decision sciences," or "business and management" or as "multidisciplinary," and, finally, papers that are classified as short papers or editorial articles. Consequently, all screened articles from the exclusion process were evaluated for their relevance based on the inclusion criteria. First, studies directly relevant to the RQs were primarily considered. This criterion was assessed based on their titles, abstracts, and conclusions. Second, articles that were peer-reviewed by academic journals and international conferences were included. We applied a snowball technique to maximize the possibility of inclusion for all relevant studies. Hence, articles obtained via this process were evaluated for relevance based on their abstracts and conclusions. All studies from the primary search filtered by the exclusion and inclusion criteria, incorporating qualified papers from the snowball tracking process, were further subjected to data extraction for the purposes of analysis and conclusion.

E. EXTRACT OF DATA

In this step, a data extraction form was designed according to a standard and consistent pattern. This form can be used to record all necessary data obtained from the articles relating to the RQs. All articles obtained during the previous step were thoroughly studied and analyzed for entire sections to extract all required data and information regarding the data extraction form. The extracted data are presented in Table 4.

F. ANALYSIS OF EXTRACTED DATA AND IDENTIFICATION OF FINDINGS

To analyze the extracted data in greater detail, both quantitative analysis (descriptive statistics) and qualitative analysis (narrative analysis) were implemented. The analyzed data were then applied to yield the study's findings.

G. DISCUSSION AND CONCLUSIONS

The results and findings from the previous step were examined in detail. All important information, practical implications, and limitations of this study were concluded and presented in this step.

TABLE 4. Extracted data.

Information	Extracted data
General information	Title of article, author name(s), publisher, year of publication
Specific information related to RQs	DL method/technique, barcode type, dataset, finding, challenge, and limitation

IV. RESULTS AND DISCUSSION

The systematic procedures identified in the previous section were applied. Only significant results from the processes identified in the previous section are presented. Fig. 2 offers an overview of the search results. Based on the predefined keywords, operators, and focused time range, the latest search was conducted in November 2021, and the search results obtained from SCOPUS and Web of Science (WoS) identified 3,275 potential studies. Following the removal of duplicates, the potential studies were reduced to 3,209 records. These papers were then further screened and filtered to 2,180 and 21 studies based on the exclusion and inclusion criteria, respectively. This significant drop in the number of articles may be attributed to two major causes: (1) approximately 20% of articles were filtered out because they were classified as reviews, book chapters, books, notes, short surveys, editorials, and letters and (2) around 75% of articles were excluded based on their lack of conformity with the research questions and the scope of the study.

In light of this topic's recent popularity and to ensure that this study covered all relevant studies, we used broad search terms and their acronyms. In the search process, we used the acronym of deep learning, "DL", as one of the primary search terms. This keyword generated numerous articles unrelated to deep learning, including papers that included words containing the adjacent letters "dl", (e.g., "rapidly", "regardless", "middle"). Approximately 75% of collected articles were excluded from the screening process, because these studies only used or mentioned barcodes but did not apply the D-CNN method to barcode recognition.

To maximize the likelihood of finding relevant studies, the snowball technique was implemented, and five studies were extracted. Therefore, the final number of relevant articles was 26. This number seems adequate compared with other recent literature review studies relating to D-CNN's application in other specific topics, as Table 2 details. These similar studies explored D-CNN-related articles ranging from 12 to 27 papers These limited number of reviewed studies seem to be usual for the recent popular topics. Nevertheless, based on the recent increase in publications on DL and their significant contributions to the related research fields, these studies were accepted and published in high-quality international journals indexed by both the SCOPUS and WoS databases.

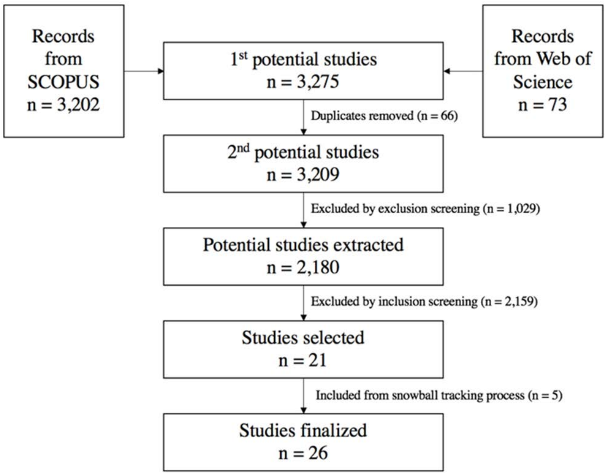

FIGURE 2. Search results from the SLR process.

A. DESCRIPTIVE ANALYSIS

In this section, the results from the quantitative or descriptive analysis of the reviewed articles are presented.

Fig. 3 illustrates the distribution of the focused studies according to the year of publication. It is clear that studies on DL in barcode recognition began in 2015. During the first two years, only one article was published per year, accounting for only 7.69% of all publications included in the literature review. Interestingly, more than half of the studies (approximately 69%) were published during the last three years—that is, between 2019 and 2021. Regarding the duration of our study, the number of articles obtained from 2021 was lower than that in 2020. This is likely attributable to the publication time of papers up to the beginning of November 2021. However, the high proportion of publications during the last two years highlights the recent surge of interest in this topic.

Table 5 presents the distribution of publication sources during the period 2015–2021. Most studies—approximately 65% (17 papers)—were published in conference proceedings, whereas articles published in journals accounted for 35% (9 papers). Each conference could publish only one related article, with the exception of the IEEE International Conference on Pattern Recognition, which could publish up to two papers on this topic. Similarly, all journals published only one qualified paper per journal, with the exception of the journal of *Multimedia Tools and Applications*. Among the various journals and conferences, publication sources directly affiliated with IEEE could publish more papers more than

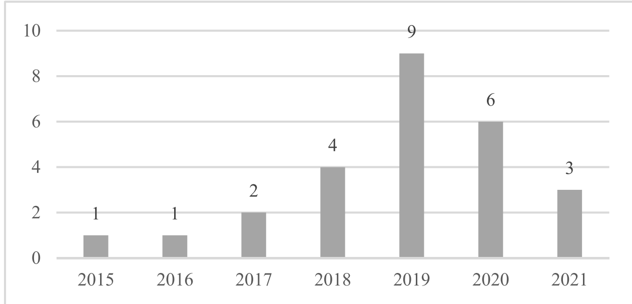

FIGURE 3. Number of articles published by year.

TABLE 5. Number of articles published by publication source.

Publication sources	No. of studies
Journal databases searched	**9**
Multimedia Tools and Applications	2
Applied Science	1
Electronic Imaging	1
Future Internet	1
IEEE Access	1
IEEE Journal of Selected Topics in Signal Processing	1
IEEE Robotics and Automation Letters	1
Journal of Advances in Information Technology	1
Conference databases searched	**17**
Conference series of IEEE (7 papers)	
- IEEE International Conference on Cyber-Enabled Distributed Computing and Knowledge Discovery, CyberC	1
- IEEE International Conference on Image Processing	1
- IEEE International Conference on Multimedia & Expo Workshops	1
- IEEE International Conference on Pattern Recognition	2
- IEEE East-West Design & Test Symposium	1
- IEEE Visual Communications and Image Processing	1
International Conference on Advanced Robotics and Intelligent Systems	1
International Conference on Cognitive Systems and Signal Processing	1
International Conference on Image Processing Theory, Tools and Applications	1
International Conference on Information Systems and Computer Aided Education	1
International Conference on Intelligent and Interactive Systems and Applications	1
International Conference on Omni-layer Intelligent Systems	1
International Joint Conference on Computational Intelligence	1
International Workshop on Document Analysis Systems	1
Logistic Journal: Proceedings	1
Unknown Conference (obtained from arXiv.org)	1

other databases (seven conference papers and three journal articles affiliated with IEEE).

Across the 26 selected articles, 97 researchers wrote about barcode recognition using DL methods, and 87 authors (89.69%) had published only one paper on this topic. This situation signifies a high degree of discontinuity in research on this particular modern topic. Only four authors (4.12%) had published more than three articles, and these researchers belonged to only one group from Shanghai Jiao Tong University, China. Twenty-two researchers (22.86%) had published one paper as the first author, and only two first authors—Zhang Jiahe and Suh Sungho—had published up to two papers on this topic. However, six co-authors had published more than one publication. Fig. 4 details the top researchers who have authored more than one article on this topic. Analysis of authorship collaboration, illustrated in Fig. 5, revealed that all articles were prepared by groups of researchers, with the exception of one small-scale study (only one barcode sample) authored solely by Tan Hanzhong [38]. Interestingly, over half of the relevant articles were published by groups of authors, including groups of more than three persons. This suggests that interdisciplinary engagement and collaboration are key characteristics of this research area.

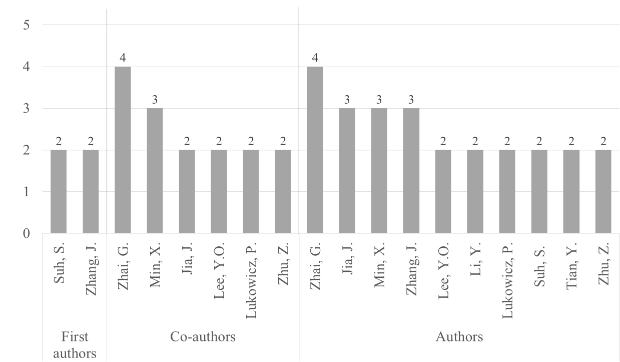

FIGURE 4. Number of articles per author (only more than one author/author).

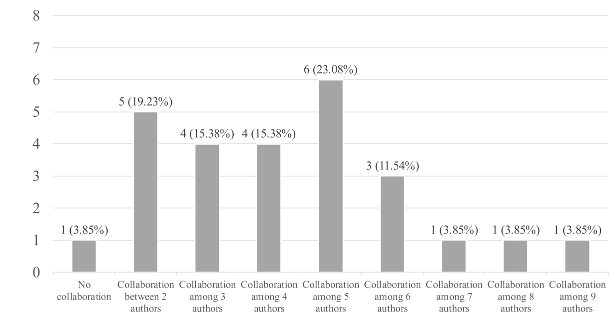

FIGURE 5. Number of articles (% of articles) with authorship collaborations.

The information presented above reveals several interesting findings from the descriptive analysis. However, this section only demonstrates the trends and general characteristics of the reviewed studies. To extract more detailed information pertaining to DL in barcode recognition, the data collected from 26 papers were further analyzed in accordance with the RQs. The insights derived from this analysis are presented in the following subsections.

B. RQ1: "WHAT TYPE OF BARCODE AND DL (CNN) METHODS WERE USED IN THE BARCODE ANALYSIS LITERATURE?"

The results of the extracted data pertaining to RQ1 are illustrated in Fig. 6 and Fig. 7 and in Table 6.

Fig. 6 depicts the overall analysis of the leading DL methods applied in the reviewed articles with respect to barcode type. As Fig. 6 illustrates, most papers specifically analyzed 1D barcodes (11 papers), whereas the second most concentrated group of studies inclusively examined both 1D and 2D barcodes (10 papers). A group of papers focusing exclusively on the topic of 2D barcodes was the least studied (5 papers). The high utilization of 1D barcodes emphasizes their significance, echoing previous works' [39] observation that 1D barcodes are more robust and reliable in real-life situations and industrial environments.

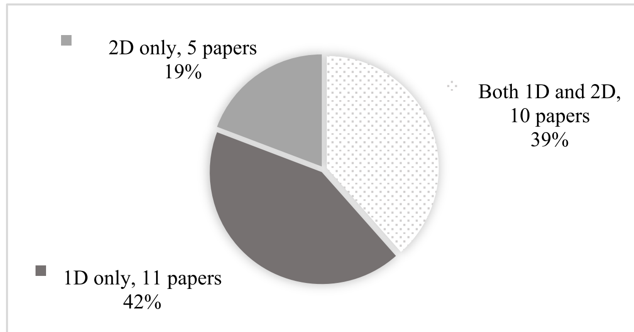

FIGURE 6. Type of barcode recognition of articles.

Table 6 presents further key details pertaining to RQ1, including the types of barcode recognition and the main DL methods applied in the reviewed articles. For example, article no. 13 [40] applied the faster R-CNN as the core DL method to analyze two types of 1D barcodes—UPC-A and EAN (EAN-8 and EAN-13)—and one type of 2D barcode: the QR code. Most proposed methods that could analyze 1D barcodes were able to detect and/or decode more than one 1D barcode type. Eighteen of the 21 papers (approximately 86%) examined at least two 1D barcode types. For example, the method proposed by article no. 19 [16] could simultaneously analyze three 1D barcode types: UPC-A, EAN-13, and Code128. The development of algorithms and methods capable of detecting and/or decoding various types of 1D barcodes represents the necessity of practical usability in real-life situations. In line with this, various 1D barcode types have been applied in several commercial applications [41]. By contrast, most of the studies selected (12 of 15 papers, 80%) examined only one type of 2D barcode at a time. Ten of these (10 of 12 or approximately 83%) focused specifically on QR code analysis. This specific concentration indicates the significance and prevalence of QR codes over other 2D barcodes, which was also emphasized in several earlier studies [42], [43]. The last category of articles proposed methods that could simultaneously analyze both 1D and 2D barcodes. Similar to the findings mentioned above, most papers in this group could analyze multiple 1D barcode types, whereas they could examine only one type of 2D barcode: QR codes. This result also confirms the above finding and points out that the concentration of barcodes still depends largely on several types of 1D and one specific 2D barcode—the QR Code.

TABLE 6. Details of barcode recognition of reviewed papers.

			Type of barcode																		Type of barcode recognition		
			1D												2D								
Article no.	Ref.	Year	Australian Post	Code128	Code39	Code93	Codebar	EAN	Interleaved 2of5	ITF	KIX Code	POSTNET	RSS 14 Expanded	UPC	QR code	DataMatrix	PDF417	Aztec	Codablock	Maxicode	Locating	Decoding	Main deep learning method
01	[36]	2015													✓						✓	×	CNN
02	[44]	2016						13													✓	×	CNN
03	[45]	2017						13						A							✓	×	Faster R-CNN
04	[46]	2017						13						A	✓						✓	✓	YOLO v2
05	[47]	2018		✓				13								✓					✓	✓	SSD
06	[48]	2018						13						A	✓	✓	✓				✓	✓	R-CNN
07	[49]	2018						13													✓	×	CNN
08	[50]	2018												A	✓						✓	×	CNN
09	[15]	2019		✓	✓			8,13		✓				A, E	✓						✓	✓	SSD
10	[8]	2019		✓				13													✓	✓	CNN
11	[7]	2019						13						A							✓	×	YOLO v2
12	[37]	2019													✓						×	✓	CNN
13	[40]	2019						8,13						A	✓						✓	×	Faster R-CNN
14	[51]	2019													✓						✓	×	SSD
15	[52]	2019													✓						✓	×	R-CNN
16	[53]	2019														✓					✓	×	DSC
17	[54]	2019			✓			8,13					✓								✓	✓	YOLO v2
18	[17]	2020		✓	✓																✓	✓	CNN
19	[16]	2020		✓				13						A							✓	✓	YOLO v3
20	[55]	2020						13,14						A	✓						✓	✓	Faster R-CNN
21	[56]	2020						13						A	✓						✓	✓	Fast R-CNN
22	[38]	2020		✓																	✓	×	CNN
23	[57]	2020	✓	✓				8,13			✓	✓			✓	✓	✓	✓		✓	✓	×	CNN
24	[58]	2021		✓	✓					✓											✓	×	CNN
25	[59]	2021						13													✓	✓	YOLO v3
26	[60]	2021			✓	✓		13	✓					E	✓	✓	✓	✓			✓	×	YOLO v4

Since the detection process aims only to locate the barcodes in images, this procedure is still unable to support barcode data extraction. Therefore, to realize the main objective of barcode recognition, the decoding process is another critical task. Table 7 and Fig. 7 present the decoding methods applied in studies relating to DL and barcode recognition. Focusing on the decoding capabilities, an open-source library ZBar was the most applied method (five papers or approximately 39%). The ZBar library could decode both1D and 2D barcodes and their subtypes, including EAN-8, EAN-13, UPC-A, UPC-E, Code39, Code128, Interleaved 2 and 5, and QR codes [61]. ZXing was also used (three papers or approximately 23%) and could decode more types of barcodes than ZBar, i.e., UPC-A, UPC-E, EAN-8, EAN-13, UPC/EAN Extension 2/5, Code39, Code93, Code128, Codabar, ITF, QR code, Data Matrix, Aztec, PDF417, Maxicode, RSS-14, and RSS-Expanded [62]. However, Zxing has attracted more criticism than ZBar, particularly with respect to its ease of use [63] and capabilities [46], [64], [65]. The other remaining methods (HALCON, Laser scanner, WeChat, QuickMark, Matrox Image Library, and QR Droid) were each used once in different studies. Although the frequency with which the methods were applied, as shown in Fig. 7, represents the decoding methods' higher capabilities; rather, the methods applied mainly depend on the studies' objectives. For example, one of the studies applied ZXing to test QR codes owing to mistrust of the capability of Zbar [46], and another study focused on ZXing because ZXing is unable to decode blurred barcodes [16]. Therefore, to identify the method corresponding to specific situations or objectives, diversified decoding methods were applied to compare the results [46]. This solution is also a general approach used in many studies in non-DL based barcode recognition [56], [64].

As mentioned above, barcode recognition broadly involves two major tasks: locating and decoding. All DL techniques applied in the reviewed studies are detailed in Fig. 8.

Fig. 8 illustrates various D-CNN based methods applied in barcode recognition studies. Among them, CNN has been the most frequently applied to this topic (ten papers, or approximately 38%), whereas YOLO was the second most applied technique (six papers, or approximately 23%). SSD and Faster R-CNN were equally adopted in the barcode recognition studies (three papers per method, or approximately 12%). R-CNN (two papers or approximately 8%), Fast R-CNN (one paper or approximately 4%), and depth-wise separable

TABLE 7. Decoding methods applied in reviewed papers.

Article no.	Type of barcode		Decoding methods (Libraries, modules, software, or tools)
	1D	2D	
04	✓	✓	ZXing and ZBar
05	✓	✓	HALCON (Software)
06	✓	✓	ZXing
09	✓	✓	ZBar
10	✓	×	ZBar
12	×	✓	ZBar
17	✓	×	Matrox Image Library (MIL)
18	✓	×	Laser scanner (Zebra DS3608ER)
19	✓	×	ZXing
20	✓	✓	Wechat (Mobile application)
21	✓	✓	QuickMark and QR Droid (Mobile applications)
25	✓	×	ZBar

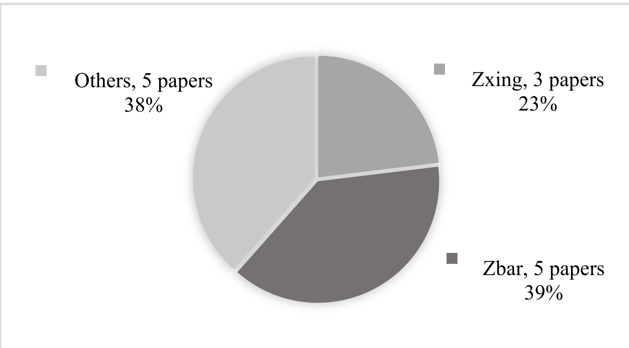

FIGURE 7. Type of decoding methods.

convolution (DSC) were the least commonly applied D-CNN methods.

Although CNN was the most widely applied method, in the latest year reviewed, only one study applied CNN to a barcode recognition task (60% of CNN studies were published before 2020), similar to R-CNN. This finding indicates a regression of CNN and R-CNN applications. Both CNN and R-CNN represent the first generation of D-CNN techniques in the CV. However, they continue to be affected by several basic issues [66], [67], which result in inefficient quality and speed during analysis. To address these problems, Fast R-CNN and Faster R-CNN were proposed. Faster R-CNN's performance (speed of analysis) was higher than that of R-CNN and Fast R-CNN by approximately 250 times and 25 times, respectively [10]. Therefore, most of the papers that applied these two methods were published during the recent years (2019 and 2020). These three methods have mainly been applied in recent years, similar to DSC, SSD, and YOLO. This finding reveals the trend in the application of DL methods to barcode recognition. Among these various approaches, YOLO is a widely and currently applied and accepted technique, particularly for swift or real-time object detection, which is suitable for barcode recognition in real-life situations [16]. Therefore, possibly as a result of this, more than 66% of articles published in the last year (2021) applied YOLO in the barcode analysis task. YOLO has been continuously optimized since the first version was debuted in 2015 [68], and the current version is YOLO version 5 [69]. However, the most recent barcode recognition study in 2021 also applied YOLO version 4 [16]. This finding indicates opportunities for improvement based on the application of new D-CNN approaches, which may lend higher speed or quality to barcode recognition.

Detailed analysis of the applications of D-CNN methods in the reviewed papers revealed that the D-CNN approaches were merely and directly applied to localize barcodes during the detection process. During the decoding process, however, D-CNN methods were only used for preprocessing. The methods were used to improve the quality of barcodes before the barcodes were read by various decoding methods, as detailed in Table 7. Two decoding-related operations were improved in earlier works: the deblurring and rotating process. Although DL's significant capabilities highly benefit image processing task, DL applications seems to be overlooked with respect to the barcode decoding process. This finding highlights important opportunities to study and improve the barcode decoding process, which also echoes findings from earlier work [37].

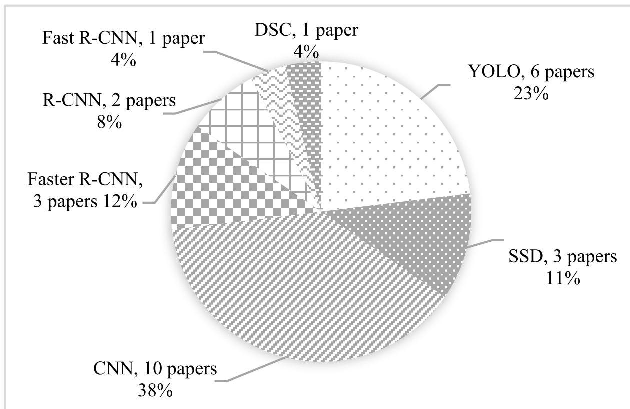

FIGURE 8. Type of main deep learning methods.

This section includes a comprehensive literature review to provide an up-to-date status assessment of D-CNN methods applied in the barcode recognition literature. Several undiscovered findings and improvement opportunities were revealed and proposed. In the next section, the barcode datasets applied in DL and barcode analysis studies are examined to explore the data sources.

C. RQ2: "WHAT DATASETS WERE USED IN THE LITERATURE?"

The accuracy and effectiveness of DL models relies primarily on high-quality datasets [13]. Likewise, one of the major challenges of barcode detection based on the DL approach is the data used in the learning process [14]. Regarding RQ2, we present barcode resource datasets that are commonly used for training and testing. Several datasets identified and used in the existing literature are briefly introduced in Table 8. Based on the study by Mashrur Mahee *et al.* (2019) [70], datasets for barcode recognition can be collected from primary and secondary sources. Their study employed the primary source's datasets for detection purposes, whereas the secondary source's dataset benefitted the decoding process. Inspired by their study, we generalize the barcode data sources and classify them into two major categories: a public resource dataset and a private resource dataset.

As Table 8 illustrates, the public resource dataset is most frequently used for barcode recognition. Public datasets are open product barcode data that are made available for public use. Their detailed description has appeared in many review articles, such as [12], [71], [72]. The datasets that fall within this class are considered secondary sources or reusable data. They have already been collected and applied by other studies. Thus, public datasets can assist researchers in evaluating their proposed barcode recognition methods because they are easy to access and can be applied directly to certain areas in scientific research.

The private resource dataset is also the primary source for barcode datasets, most of which are unavailable for public use. The dataset can be accessed by the owner or users with appropriate permission. Some may be commercial databases that require a subscription before use, such as the GS1 Company Database (GEPIR) [73]. Private datasets are considered an excellent solution when no proper data collection fits the training purposes. In recent decades, private barcode datasets may include barcode images gathered from the internet, images captured using mobile cameras, scanned documents, screenshots, and images acquired from production lines, warehouses, and retail stores.

The public resource dataset sometimes contains insufficient features for the learning process. At the same time, most private resource datasets are labor-intensive, as they require extensive effort to obtain labeled barcode images in actual practice. Moreover, datasets from both classes may suffer from crashes when operating in real-world environments. Therefore, a synthetic resource dataset generated from a virtual environment can be used as an alternative solution. Synthetic barcode datasets can be generated and opened for public purposes or created specifically for private use. However, the straight computer-generated barcode may not be useful, as it misses out on various conditions found in real-world barcode images [70]. Therefore, to maximize synthetic barcode datasets, the research should consider the optimum conditions for creating the datasets.

In accordance with RQ2, Table 8 presents the detailed information pertaining to barcode datasets, including each dataset's sample size, the resolution of the barcode images, the number of barcodes in each image, the electronic devices used to capture the barcode images, and the type of barcodes included in the dataset. The table also shows the number of papers that employed at least one of the datasets. As outlined in the table, all barcode datasets range in size from several hundred to over twenty-thousand samples. The datasets primarily include image frames of 1D or 2D barcodes captured from various smartphone cameras, rather than industrial cameras. Hence, the original barcode images with low or high resolution depended on which camera and photo modes were used. Note that the size of the dataset and the resolution of barcode images could refer to the dataset's quality, which directly affects the learning process. Most of the time, the choice of blurry and low-quality images is reasonable, since it makes the dataset more challenging for DL-based barcode detection algorithms. It can also be observed that the number of barcode datasets that include both 1D and 2D barcodes is limited. This is because, in most cases, 1D and 2D barcodes can be read using different types of technology and are commonly applied in different applications. More importantly, state-of-the-art methods are specifically proposed for solving barcode problems in individual domains, enabling researchers to conveniently collect barcodes from real-life situations by focusing on a single barcode type.

Of the six public barcode datasets presented in Table 8, WWU Muenster, ArteLab, and the Dubská M. dataset [74] acquired greater popularity than others. The datasets include a sufficient number of barcode images with standard resolutions that significantly boost DL performance. On the contrary, the Bodnár-Synthetic dataset [75] was of little concern to the present research topic. Two key reasons for this may be the first, that the dataset contains synthetic barcode images that are not realistic and thus can compromise the learning process and decision-making based on the data and second, that the dataset is novel and unfamiliar to scholars. With the increased interest in 2D barcodes at present, we believe that this dataset will likely be expanded for future research and may play an essential role in DL-based barcode recognition. The Bodnár M. dataset is a rich synthetic barcode dataset with 10,000 barcode tags rendered against diverse backgrounds. Leastwise, integrating their barcodes with realistic image backgrounds would allow the DL model to learn efficiently from a massive amount of barcode data.

As mentioned previously, several available online datasets can be easily accessed and freely utilized. In the most current scientific research on barcode recognition, however, all datasets could only be applied for general purposes, such as simple or direct barcode detection in general environments and situations. More specific analytical purposes, such as improved image deblurring or skewing in specific domains, still require different image features for barcodes or environments. This suggests that various datasets consisting of specific barcodes, environments, or contexts for public use, such as barcode images captured by UAV in the closed warehouse, are required.

Unsurprisingly, regarding the current limitations of public datasets, various private datasets have been developed by several studies for different and specific purposes. All private datasets were each exploited once in different studies. The dataset may comprise the original photos taken by mobile phone cameras, industrial cameras, and images captured from video sequences [52]. Some of them are barcode images

TABLE 8. The detailed information of different barcode datasets found in all reviewed papers.

	No.	Dataset	Size	Resolution (pixel)	Instance per image	Record device/ Image source	Barcode type	Applied domain	No. of papers
Public resource dataset	1	Arte-Lab Medium Barcode 1D Collection (MBC) [76]	215	640 × 480	Single	Nokia N95	1D	General	8
	2	Arte-Lab Rotated Barcode Database [77]	365	640 × 480	Multiple	Nokia N95	1D	General	2
	3	WWU Muenster [78]	1055	640 × 480	Multiple	Nokia 5800 and others	1D	General	9
	4	Dubská M. [74]	400	604 × 402	Single	Webcam and Mobile phone cameras	2D	General	4
	5	Sörös G., and Flörkemeier [79]	320	720 × 1280	Single	iPhone 5 and iPhone 4S	1D, 2D	General	4
	6	CipherLab QR dataset	125	-	Multiple	Images provided by Cipherlab	2D	General	3
	7	Bodnár-Synthetic [75]	10,000	512 × 512	Single	Computer generated	2D	General (Synthetic)	1
Private resource dataset	8	UAV barcode [17]	537	512 × 512	Multiple	Raspberry Pi Camera v1.0 and v2.0	1D	Industry	1
	9	UAV123 [52]	5,000	-	Single	Images captured from video sequences	2D	Industry	1
	10	QR tags on COCO Val2017 [52]	5,000	-	Single	-	2D	Industry	1
	11	Mixed Barcode dataset [48]	2,000	-	Multiple	-	1D, 2D	General	1
	12	Ventsov, N. N.[49]	7,520	-	Multiple	-	1D	Book & Library	1
	13	Jia, J. [55]	2,227	-	Multiple	-	1D, 2D	Retail	1
	14	Zhang, J. [56]	320	-	Multiple	-	1D, 2D	General	1
	15	Yuan B. [52]	14,000	-	Multiple	Industrial cameras	2D	Industry	1
	16	Fashion label dataset [8]	700	8 × 57, 10 × 40	Multiple	-	1D	Fashion	1
	17	Online fashion images from Poshmark [8]	1,000	-	Multiple	Images taken from Poshmark website	1D	Fashion	1
	18	Blanger, L. [51]	767	480 × 480	Multiple	Images downloaded from Internet	2D	Public Relations	1
	19	Medical Labels from Baidu and Google search [47]	400	512 × 512	Single	Images taken from Google and Baidu search	1D, 2D	Medical	1
	20	Hisense Production line [37]	100	-	Single	Canon EOS 760D	2D	Industry	1
	21	Product on the racks at TU Dortmund University [44]	408	-	Single	Samsung Galaxy S4's camera	1D	Retail	1
	22	DPM codes [53]	2,500	-	Multiple	Industrial cameras	2D	Industry	1
	23	Air Waybill Labels (AWB) dataset [16]	25,000	4,112 × 3,008	Multiple	Industrial cameras	1D	Industry	1
	24	QR code images dataset [36]	200	-	Single	Online barcode generator	2D	General (Synthetic)	2
	25	EAN-13 [16]	25,000	640 × 480	Single	Zint barcode generator	1D, 2D	General (Synthetic)	1
	26	Barcode-30k [50]	30,000	-	Multiple	Photographed images and computer generated	1D, 2D	General	1
	27	15 Carriers Shipping Labels [54]	1,944	416 × 416	Multiple	Photographed images, document scans, and computer generated	1D	Industry	1
	28	Logistics Robot Barcodes [38]	-	-	Single	Industrial cameras	1D	Industry	1
	29	Shipping Labels [58]	6,398	416 × 416	Multiple	Smartphones and computer generated	1D	Industry	1
	30	ZVZ-Synth [57]	30,000	512 × 512	Multiple	Computer generated	1D, 2D	General (Synthetic)	1
	31	ZVZ-Real [57]	971	512 × 512	Multiple	Photographed images and document scans	1D, 2D	General	1
	32	Supermarket Products [59]	6,429	416 × 416	Multiple	Images downloaded from Internet and photographed images	1D	Retail	1
	33	Liwei Zhang *et al.* [60]	16,545	1,000 × 1,000	Single	Photographed images	1D, 2D	Industry	1

downloaded from search engines (e.g., Google and Baidu) [47], document scans [57], as well as websites [8] before all images were further adjusted by the researchers. From this aspect, we could not suggest which private datasets are

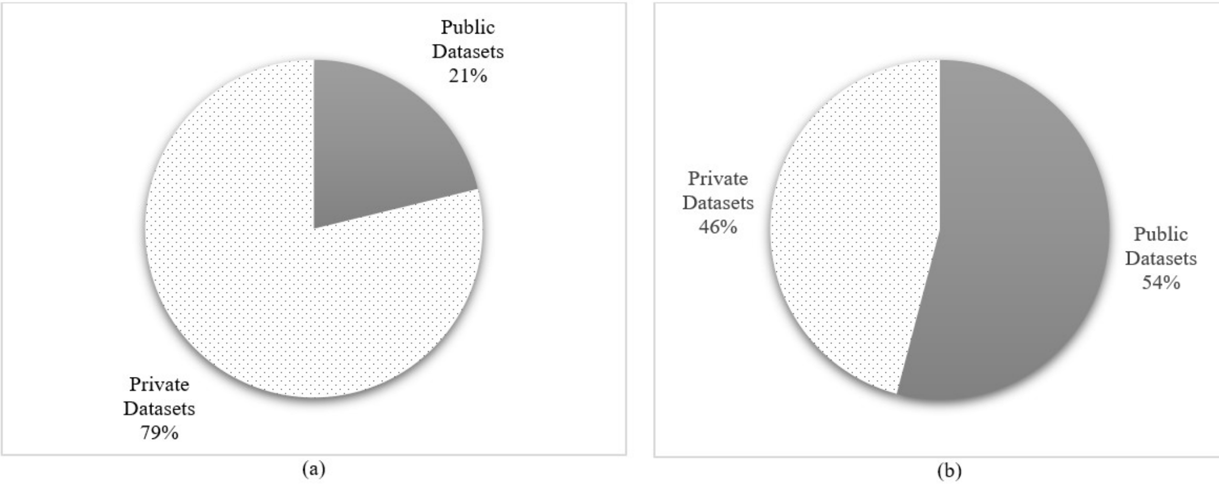

FIGURE 9. The proportion of barcode datasets in two distinct classes: (a) the number of public datasets and private datasets, (b) the frequency of employing public datasets and private datasets.

most useful, as private datasets rely heavily on the criteria of the data collection phase. The researchers must prepare adequately to ensure that the dataset meets the research scope and aligns with the learning process.

The comparison of different classes of barcode datasets (public and private) used for DL-based barcode recognition is represented in Fig. 9(a). Of the 33 datasets found in the focused articles, seven (21%) are datasets from public sources. By contrast, the private resource dataset accounts for 26 datasets (79%) and is almost three times greater than the group of public datasets. We explored the relative frequency of barcode datasets implemented in all reviewed articles and counted one whenever a distinct dataset was used in each article. Then, we summarized the number of times the dataset was applied across different articles. As Fig. 9(b) illustrates, the values in parentheses next to the data label indicate how often the datasets in public or private sources were reused. The high proportion of public datasets shown in Fig. 9(b) implies high popularity (54% of occurrences).

Although the available public datasets are not varied, the datasets were reused repeatedly by many scholars. Conversely, many private resource datasets are available, but private datasets are rarely employed in various articles. These findings confirmed that public datasets are the most popular resource for DL-based barcode detection, requiring only a few attempts to obtain the dataset. Flexible data access through online sources granted convenience to the researchers. Furthermore, the results obtained from the utilization of public datasets could be applied to benchmarking studies or models applying the same datasets. The advantages and popularity of public resource datasets highlight the high demand for open databases for barcode analysis.

Considering the barcode datasets in different domains, we have categorized all observed datasets into seven groups: a group of barcode datasets used in the industry, fashion, medical, retailing, book and library, Public Relations (PR),

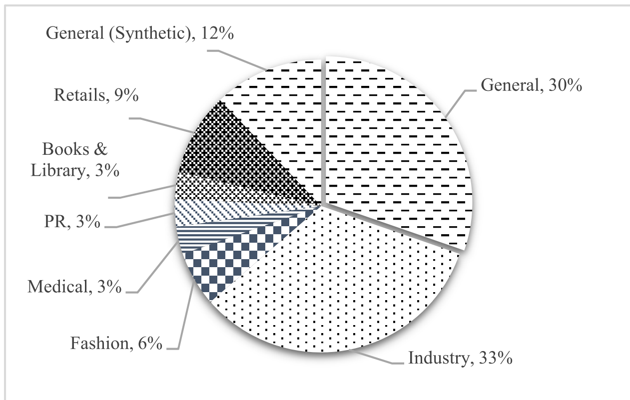

FIGURE 10. Barcode dataset applied in different domains.

and general domains. As Fig. 10 shows, fourteen datasets (42%) found in the literature were applied in the general domain (unspecified domain of interest). Four datasets (12%) included in the general domain are synthetic and are typically unlimited with respect to the expansion of their application into various domains. The following is the dataset from an industrial area that yields eleven datasets (33%). Industrial barcode images may include barcodes attached to parcels in the warehouse, barcode tags on manufactured materials or products in production lines, and images captured by UAV cameras. Three datasets (9%) from the retail domain contain barcode images attached to consumer products. Retail-related barcode images were primarily collected from grocery stores or captured from several products used in daily life or finished goods. Nevertheless, two datasets (6%) that fall within the fashion domains contain barcodes on the price tags of clothes collected from online and on-site shopping stores. In the field of PR, the barcode images were gathered from the Internet, most of which are 2D barcodes that are weblinks allowing users to access information directly. The remaining datasets in the book and library and medical domains are similar to those in the PR domain. However, they are more specific and have hitherto received little attention (one dataset is found in each domain).

Compared to the other domains, Fig. 10 demonstrates that the datasets used for studies in the general and industrial domains are key research resources for this topic. The datasets in both domains are not only counted as the most frequently used datasets for DL-based barcode detection, but they can also be implemented in a wide range of studies relating to barcode technology. The classification of datasets according to the origins of their creation, their applications, and their frequency of use may indicate the popularity of domain categories, which were either largely concentrated (e.g., industry) or less studied (e.g., medical). Several studies have utilized barcode datasets and DL to improve barcode recognition across various domains. Unfortunately, some domains that rely heavily on barcode applications, such as banking or financial services [80], [81], still lack directly specific and concordant datasets. It is also rare to observe the adoption of DL in the mentioned domains. Therefore, these findings highlight several improvement opportunities for datasets' development and availability and their domains of application.

Fig. 9 reveals the overall number and utilization frequency of datasets in the public class against that of datasets from the private class, whereas Fig. 10 shows several datasets applied in different domains. However, the information may not offer profound insight into dataset adoption, particularly in the most recent DL-based articles for barcode analysis. Several questions remain, such as how many datasets are used in each article and what the dataset's utilization patterns are.

Conducting in-depth analysis of the above issues, we first examined the number of datasets adopted in each paper, as summarized in Table 9. Note that the barcode datasets adopted by the current research are not restricted to the two major classes of real-world barcodes (public or private) but also the synthetic ones. The synthetic barcode datasets may be public or private. They are typically applied to strengthen the research topic and confirm the effectiveness of the proposed model. Considering a group of synthetic datasets may help represent a broader perspective of dataset utilization. Therefore, we have also discussed the use of synthetic datasets, regardless of whether they are in the public or private class. Accordingly, n_{public} is the number of datasets in a public class, $n_{private}$ denotes the number of datasets in a private class, $n_{synthetic}$ refers to the number of synthetic datasets, and n_{total} stands for the total number of datasets adopted in each article.

As Table 9 demonstrates, most articles on DL-based barcode recognition employed at least two datasets, specifically those that used the datasets from the public class. Comparing each article's n_{total}, we found that article no. 20[55] employed the highest number of datasets (six datasets were used in their experiments).

We also investigated the distribution of datasets used independently or applied inclusively to other datasets. We declare the distribution of barcode datasets based upon three classes:

TABLE 9. The number of datasets used in each article.

Article no.	n_{public}	$n_{private}$	$n_{synthetic}$	n_{total}
01	1	-	1 (private)	2
02	-	1	-	1
03	2	-	-	2
04	4	-	-	4
05	-	1	-	1
06	2	1	-	3
07	-	1	-	1
08	-	-	1 (private)	1
09	3	-	-	3
10	-	2	-	2
11	2	-	-	2
12	-	1	-	1
13	4	-	-	4
14	-	1	-	1
15	1	3	-	4
16	-	1	1 (private)	2
17	2	1	-	3
18	-	1	-	1
19	3	1	1 (private)	5
20	4	1	1 (public)	6
21	4	1	-	5
22	-	1	-	1
23	-	1	1 (private)	2
24	-	1	-	1
25	-	1	-	1
26	-	1	-	1

public, private, and synthetic. From this perspective, the label number that appeared in Fig. 11 indicates the number of articles that employed single- or multi-class barcode datasets. For example, article no. 19 [16] and article no.20[55] adopted at least one dataset from each class: public, private, and synthetic. Thus, these two papers are counted as members of public + private + synthetic.

As Fig. 11 illustrates, several DL papers relied on private datasets. This is because it is easier for scholars to customize barcode images for their specific needs, giving them total control of their dataset directly and facilitating more precise research. By contrast, the present study, which based its experimental analysis on a single synthetic dataset, is more unusual. The reason is that training or testing the model over the generated synthetic barcode images may have biased the learning process and relied on the expected outcome. Interestingly, the portion of papers that exclusively employed public datasets was smaller than those that employed private datasets, even though datasets from public sources are clarified as the most frequently used. Only one paper verified the proposed DL method on the public + synthetic datasets. Two and three papers worked across the public + private + synthetic, private + synthetic, and public + private datasets, respectively.

As Table 9 demonstrates, the distribution of dataset adoption in Fig. 11 guides the direction to future research topics by considering the distinct conditions of barcode datasets. It is believed that applying different datasets, whether from the same or different classes, can foster the development

TABLE 10. Dataset usage schemes in two different purposes: model development and benchmarking purposes.

Article no.	Model development purpose			Benchmarking purpose			
	Split a dataset for training and testing	Use a different dataset for training & testing	Use more than one dataset for training or testing	Use a subset of data for benchmarking	Dataset(s) used for model development is/are different from one(s) used for benchmarking	No benchmarking with other datasets	Use more than one dataset for benchmarking
01	✓	-	-	-	✓	-	-
02	✓	-	-	✓	-	-	-
03	✓	✓ (Partially)	-	-	-	-	✓
04	✓	-	✓	-	✓ (Partially)	-	✓
05	✓	-	-	✓	-	-	-
06	✓	-	-	-	-	-	✓
07	✓	-	-	✓	-	-	-
08	✓	-	-	✓	-	-	-
09	✓	-	✓	-	-	-	✓
10	✓	-	-	-	✓	-	-
11	✓	-	✓	-	-	-	✓
12	✓	-	-	-	-	✓	-
13	✓	-	✓	✓	-	-	✓
14	✓	-	-	-	-	✓	-
15	✓	-	✓	-	✓ (Partially)	-	✓
16	✓	-	-	-	-	✓	-
17	-	✓ (Partially)	-	✓	✓	-	✓
18	✓	-	-	-	-	✓	-
19	-	✓ (Partially)	✓	-	✓	-	✓
20	✓	-	-	-	✓	-	✓
21	✓	-	✓	✓	-	-	✓
22	✓	-	-	-	-	✓	-
23	✓	-	✓	-	-	-	✓
24	✓	-	-	✓	-	✓	-
25	✓	✓	-	✓	-	✓	-
26	✓	-	-	-	-	✓	-
	24	**4**	**8**	**9**	**7**	**8**	**12**

of the DL model. They could ensure the proposed methods can resist some distortions and diverse qualities of the barcode images contained in different datasets. As mentioned in [55], [56], experimenting on various datasets could verify the effectiveness of the proposed layers, giving robustness and confidence to results. We hope that applying benchmark datasets exclusively and learning from different sources can lead the barcode recognition method to a skillful model.

To study the dataset's utilization patterns, we further explore the mainstream purposes of barcode datasets and define them into two categories: the dataset's utilization pattern for model development purposes and benchmarking purposes. For each purpose, various usage schemes were found in the focused articles, as summarized in Table 10. For model development, we found that almost all studies, except article no. 17 [54] and article no.19 [16], preferred to split datasets for training and testing. Unfortunately, only four studies (approximately 15% of all focused articles) performed training and testing on different datasets. It appears that the selection of a training dataset that differs from the testing dataset may risk lowering precision/accuracy since the model is tested entirely on unseen samples.

Taking into account benchmarking purposes, nine papers used a subset of data (from the same dataset used for training/testing) to evaluate the model performance. At the same time, seven studies developed and evaluated their proposed models using different datasets. Two studies, i.e., article no. 04 [46] and article no. 15 [52] simply added another dataset to the benchmarking group, resulting in only a small difference between the model development dataset and the benchmarking dataset. Moreover, although the datasets are used separately for each purpose, their characteristics and data attributes are similar. This is evident in article no. 10 [8], in which the fashion label dataset was used to build the model,

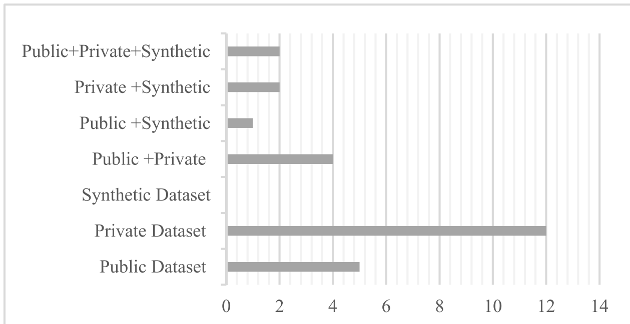

FIGURE 11. The distribution of different classes of datasets employed in the focused articles.

but the online fashion image dataset was applied to evaluate the model. Thus, the high precision/accuracy obtained from such settings could not confirm that the model's generalization ability was strong.

Continuous observation of the information in Table 10 revealed that no benchmarking appeared in eight studies, whereas the remaining studies evaluated their proposed models only on the test set. Interestingly, almost half of the articles (12 articles) used more than one dataset to benchmark or evaluate model performance. The application of multiple datasets for model development or benchmarking is considered a baseline or standard practice for current research in this area. To the best of our knowledge, the use of a single or the same dataset for training, testing, and evaluation is the simplest method but is associated with a strong risk of bias. At the same time, challenges still emerge when different datasets are used for training, testing, and benchmarking. To avoid bias and improve the generalization abilities of DL-based barcode recognition methods, we recommend that future research carefully select experimental datasets by focusing on the diversity of the dataset in various complex environments.

After selecting the barcode dataset, researchers may further format the barcode images to align with the training purposes and model inference. The techniques adopted to adjust the barcode images may include—but are not limited to—color correction, cropping, denoising, filtering, and resizing the images to fit the input layer. These techniques are known as data preprocessing and are commonly applied in both training sets and test sets [82]. In the articles reviewed, many preprocessing tasks are manipulations applied to simplify barcode recognition and the background on which the barcode is located [49]. The preprocessing step is used to speed up the DL algorithm or to ensure that the model obtains the best possible detection results. The advantages of preprocessing are evident in two aspects: first, preprocessing helps to accelerate the algorithms (e.g., angle detection, cropping, denoising, filtering, and rotation); second, preprocessing increases DL's capability with respect to generalization (e.g., assigned blurring feature, coloring/grayscale, generate new images,

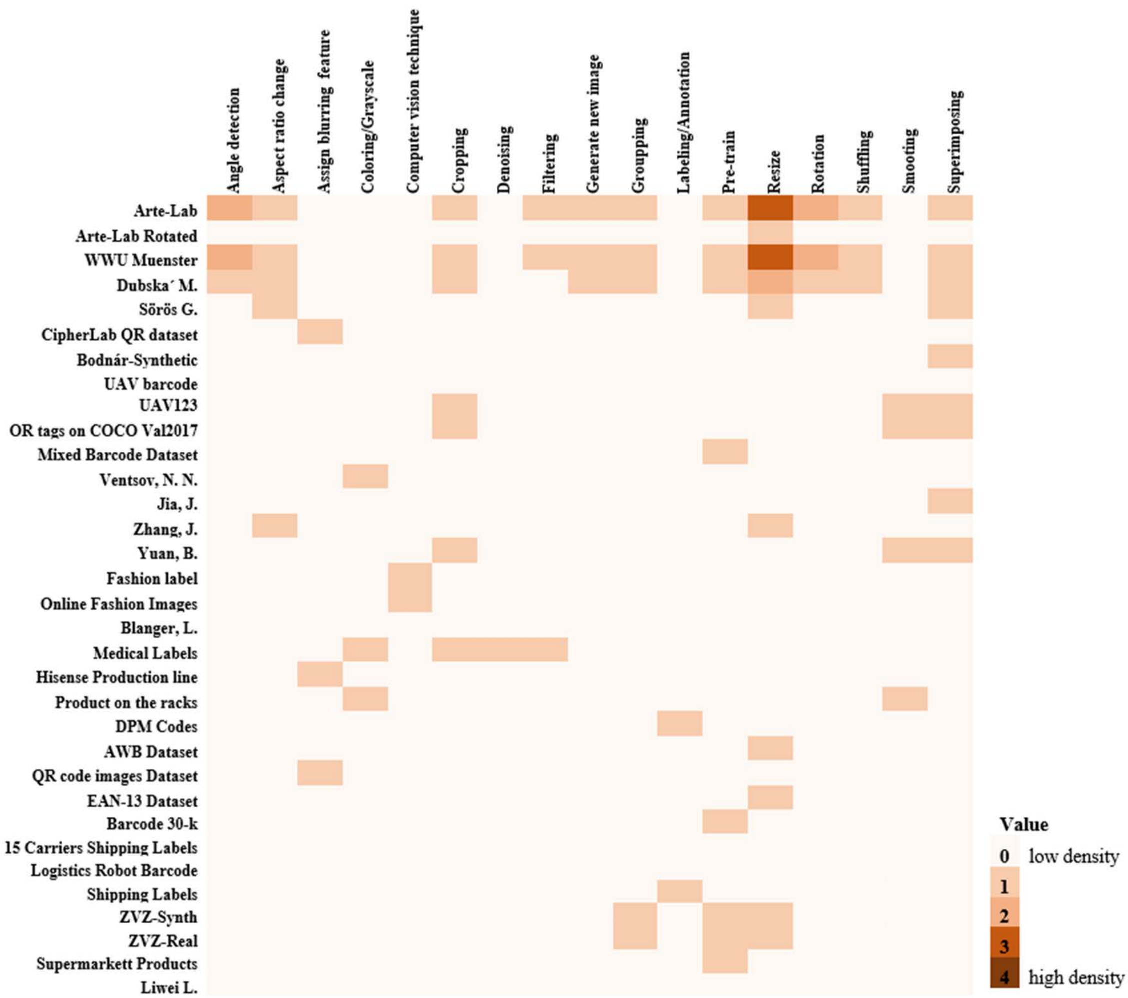

FIGURE 12. Density matrix of data preprocessing methods applied over different barcode datasets.

smoothing, and superimposing). However, some image preprocessing techniques may benefit both aspects. This situation is evident in [55], where the resizing of images allows the model to localize the barcodes more easily. Downscaling of the barcode images leads the model to improve the training speed and requires less time to detect barcodes. Meanwhile, rescaling the input images can enhance the detection accuracy. As described in [36], resizing images offers a means of creating various barcode versions that expose the model to a wider array of training examples.

In Fig. 12, we investigate the density of preprocessing methods that have been applied across different barcode datasets. A high density and wide range of preprocessing techniques can be seen in a group of public resources. Compared with other datasets, many preprocessing techniques have dramatically influenced DL-based barcode recognition methods applied to the Arte-Lab, WWU Muenster, and Dubská M. datasets. This circumstance suggests that the mentioned datasets lack specialties, refinement, and are not ready for use. This is because barcode images in most public resource datasets were generated for unconstrained environments. They are often incompatible with the learning process in specific environments. Therefore, greater effort is required to clean and simplify barcode images prior to model input. Moreover, the high density of the various preprocessing methods presented in Fig. 12 denotes the standard preprocessing methods adopted in current research. This insight guides scholars to carefully perform preprocessing methods on public barcode datasets prior to model training, such as angle prediction, resizing, and rotation.

Resizing, superimposing, and cropping are more frequently applied than other techniques. However, the UAV barcode dataset [17] and the Blanger L. dataset [51] originally maintained the same image quality. We may assume that the barcode images in their datasets were deliberately collected under various conditions and had already satisfied both the training and testing criteria. Datasets with high-quality images do not always leverage a data learning process. Sometimes, the decision to reduce image quality at the preprocessing stage (i.e., resizing, smoothing, blurring, and giving a more complex background) can significantly improve the model performance. In light of the above evidence, future research should establish better barcode image datasets by considering their suitability and adaptability to the learning process. More importantly, the invented barcode datasets should be reusable with minimal preprocessing when implemented in the new environment. This solution reduces the time and resource expenses used during the preprocessing stage and allows resources to be reimplemented for model generation.

As mentioned earlier, DL techniques offer effective solutions for barcode detection in large quantities of data through the training stage. Accordingly, data augmentation techniques are frequently used to obtain more representative training samples [56]. That is, data augmentation can provide a way to efficiently train a model with distinct conditions with respect to barcode images. Several data augmentation methods can be applied to the dataset used in the experiment—for example, rotation in different angles, horizontal/vertical flip, adjusting contrast and brightness, random cropping, changing aspect ratio, adding Gaussian smoothing or noise (i.e., lines, light spots, blur, overlays). It is worth noting that some barcode augmentation methods are forms of image preprocessing, but augmentation can only be applied to the training set.

Fig. 13 highlights the majority of data augmentation methods applied intensively over a collection of public resource datasets. It can be seen clearly on the WWU Muenster, Arte-Lab, Dubská M., and Sörös G. datasets. The high density of data augmentation signifies the data scarcity that characterized these four datasets. The small dataset size is typically responsible for the poor performance of the DL model. On this basis, we suggest that data augmentation be performed across the mentioned datasets prior to training to enrich the identification of barcode items without or with less finetuning. The density matrix also demonstrated that most of the datasets employed at least two augmentation techniques. Meanwhile, none of the augmented images were implemented across several datasets (i.e., fashion labels, online fashion images, medical label datasets, barcode 30-k, 15 carriers shipping labels, or the Liwei L. dataset [60]), which means the size of the training data or the diversity of the barcode images is considered sufficiently large. Moreover, the high density of image rotation, flipping, smoothing, and offset position denotes the key augmentation techniques for barcode analysis.

Focusing on public datasets, the available datasets include high quality and clear images with no complex background. Some lack multiple barcodes in each image. With these characteristics, the dataset may be unsuited to training purposes and may be associated with a risk that the DL model will be overfitted. For this reason, public barcode datasets require data augmentation strategies. As confirmed by [14] and [48], the application of various data augmentation methods benefits the training model with high generalization capabilities and reduces overfitting. Compared to public datasets, the employment of different data augmentation methods on private barcode datasets is scarce. This is due to the fact that the datasets are self-built. The researcher can fully control the barcode gathering procedure to satisfy the experiment's requirements, both quantitative and qualitative. Therefore, augmentation may not be necessary for the private dataset unless the number of original observations is too small and may negatively affect the DL model.

Based on a thorough investigation on the data augmentation techniques applied to different datasets, we can conclude that one of the research directions is to establish large-scale barcode datasets that contain diverse imaging conditions. Researchers wishing to create new publicly available datasets might focus on arranging different augmentations, as illustrated in Fig. 13. Although data augmentation can increase the diversity of barcode images seen in the DL model [83], too many augmented input images may negatively impact the

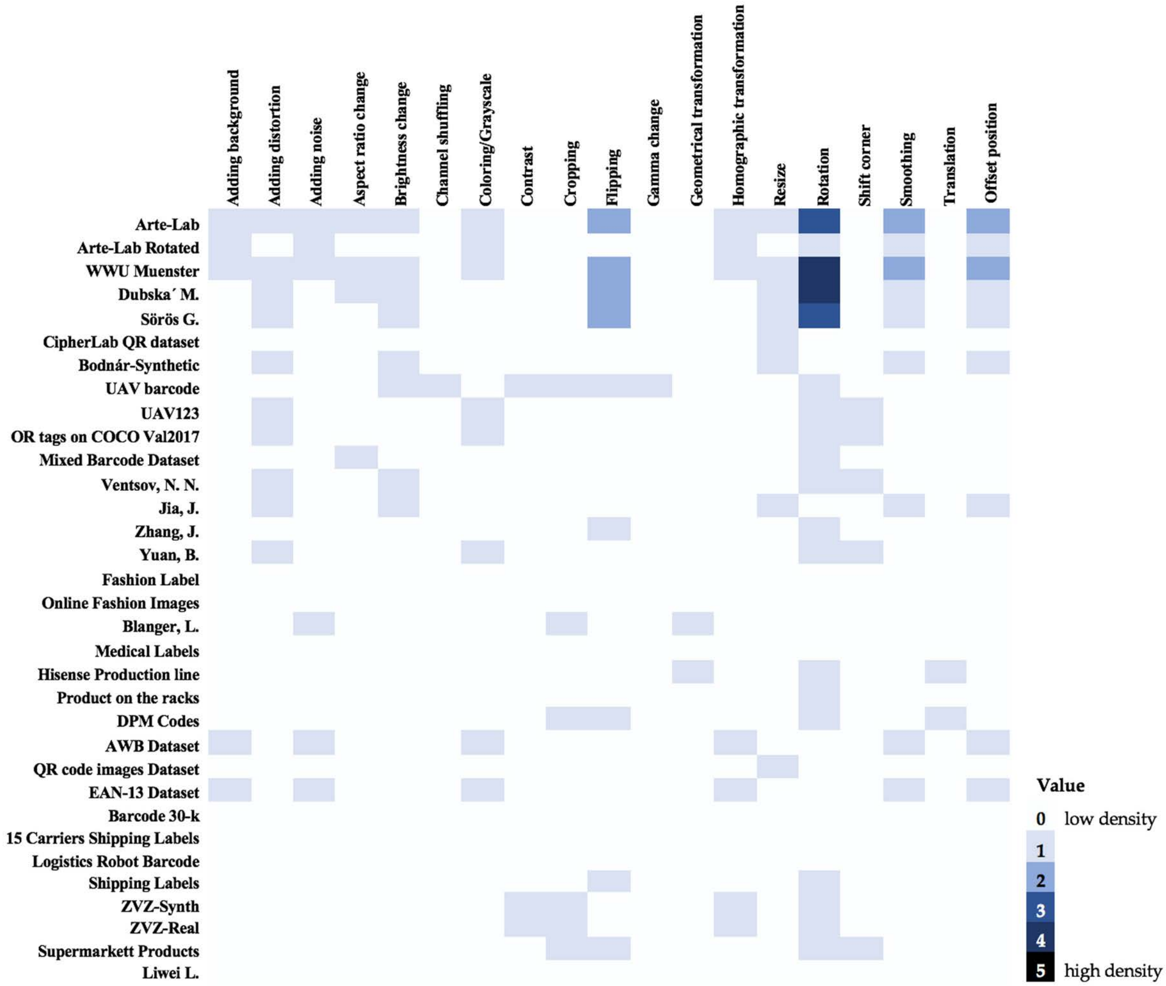

FIGURE 13. Density matrix of augmentation methods applied over different barcode datasets.

model's accuracy. Researchers should also balance the trade-off between model generalization and detection accuracy for DL-based barcode recognition. The trade-off balance execution may be realized by enabling proper image transformation operations or adopting augmentation-based generative models, as suggested in [12]. We assert that each augmentation technique has specific strengths that can adaptively improve model generalization while retaining as much accuracy as possible.

The analytical results from barcode preprocessing and augmentation techniques indicate a significant opportunity to enhance the usage of both public and private resource datasets. From this perspective, scientific scholars should focus on creating good barcode datasets and making them available for reimplementation. This action would crucially allow valuable barcode datasets to attract more attention for future research, both in terms of developing the model and benchmarking. It is also instructive that comprehensively large and suitable datasets support the areas in which the barcode recognition algorithm has made good strides. Such data are helpful in generating robust models with good generalization capabilities. However, current DL technology may require further development to enable it to handle increasingly complex problems in barcode analysis. Therefore, it is necessary to understand the challenges and limitations associated with DL-based barcode recognition, as will be discussed in the next section.

D. RQ3: "WHAT WERE MAJOR FINDINGS, AND CHALLENGES OR LIMITATIONS IN THE LITERATURE?"

Based on our extensive literature review, this section presents the findings pertaining to the third research question (RQ3): what were the major findings, challenges, and limitations in the literature? Therefore, this section is divided into two main parts: research findings and challenges or limitations.

1) MAJOR FINDINGS

This section focuses on the major goal of DL-based barcode recognition studies: the performance of detecting and

TABLE 11. Detecting and decoding performance of DL-based barcode recognition.

Article no.	Detecting						Decoding		
	One dataset scenario		More than one datasets/scenarios				One dataset scenario	More than one datasets/scenarios	
			Lowest		Highest			Lowest	Highest
	P_t, A_t, *mAP*	R_t	P_t, A_t, *mAP*	R_t	P_t, A_t, *mAP*	R_t	Decoding rate	Decoding rate	Decoding rate
01	0.9520 (A_t)	N/A							
02			0.4700 (A_t)	N/A	0.8900 (A_t)	N/A			
03			0.9890 (A_t)	N/A	0.9940 (A_t)	N/A			
04			0.7190 (A_t)	N/A	0.9540 (A_t)	N/A		0.6140	0.8070
05	0.9500 (A_t)	N/A						0.9250	0.9450
06			0.9330 (P_t)	0.9240	0.9730 (P_t)	0.9540		0.5840	0.7850
07			0.8332 (A_t)	N/A	0.9741 (A_t)	N/A			
08	0.9424 (A_t)	N/A							
09			0.8852 (A_t)	N/A	0.9945 (A_t)	N/A			
10	0.9670 (A_t)	N/A					N/A		
11			0.9120 (A_t)	N/A	0.9939 (A_t)	N/A			
12								0.9727	0.9885
13	0.8710 (*mAP*)	N/A							
14			0.6410 (A_t)	N/A	0.7700 (A_t)	0.8100			
15			0.9840 (P_t)	0.9840	0.9926 (P_t)	0.9900			
16			0.9950 (P_t)	0.9930	0.9999 (P_t)	0.9930			
17			0.7172 (A_t)	N/A	0.9805 (A_t)	N/A	N/A	0.1732	0.9627
18	0.9156 (P_t)	0.9696							
19			0.9900 (A_t)	0.9100	1.0000 (A_t)	0.9900	0.4460		
20			0.8520 (P_t)	0.8720	0.9890 (P_t)	0.9850			
21	0.8790 (*mAP*)	N/A						0.6599	0.6776
22	0.9880 (A_t)								
23			0.9778 (*mAP*)	N/A	0.9976 (*mAP*)	N/A			
24			0.8810 (A_t)	0.915	0.9930 (A_t)	0.963			
25	0.9020 (A_t)	N/A					N/A		
26	0.9230 (*mAP*)	0.9510							

decoding tasks. These findings were commonly identified and discussed in each study. The details of common performance measures of barcode recognition task are presented above in Section II (B). In most articles, either the precision rate (P_t), accuracy rate (A_t), or recall rate (R_t) were generally applied as the main matrices used to measure barcode detection performance. Concurrently, few studies adopted the mean average precision (*mAP*) [84]. For the decoding performance, the success rate was applied in all studies.

Therefore, to precisely depict the comparable performances of the works reviewed, P_t, A_t, or *mAP*, and R_t are used for the detecting process, whereas the decoding rate is applied to the decoding task.

Table 11 details the barcode analysis tasks' performance in all studies. The results of the barcode analysis tasks from each study are presented according to precision rate, recall rate, both precision and recall rate, or not available (N/A). These choices depend on the availability and measurement of the data of articles. For example, article no. 01 [36] focused exclusively on detecting barcodes and used only one dataset to test the proposed model. The experimental results of article no. 01 are expressed by the values in the P_t or A_t, and R_t column under the main column of detecting equally to "0.9520 (A_t)" and "N/A." This information signifies that the model's accuracy and recall rate are equal to 0.9520 and not available, respectively. Moreover, to benchmark the results of the proposed model with those of other models, several articles applied more than one dataset or implemented numerous testing scenarios. For example, article no. 03 [45] studied the detection of 1D barcodes and used two public datasets. That study's results presented only the detection accuracy rates of the Arte-Lab Rotated Barcode [77] and WWU Muenster datasets [78], which were 0.9890 and 0.9940, respectively. Regarding the complex results of several articles and the space limitations, the table could show only significant information obtained from the relevant studies. Therefore, to obtain more detailed information about the findings, a more comprehensive study of each article is highly recommended. For example, article no. 04's [46] results were presented in various dimensions, but Table 11 shows only the worst and best precision rates identified in the research. The article analyzed two barcode types (1D and 2D), using two (Arte-Lab rotated barcode and WWU Muenster) and three datasets (Arte-Lab rotated barcode, Dubská, and Sörös and Flörkemeier) for 1D and 2D barcode recognition, respectively. They also developed several proposed models (e.g., models with and without the bounding box).

The information provided in Table 11 indicates that the best detection rate of the proposed model from article no.19 [16] could achieve the real-life or commercial targets (100%) only for accuracy rates. However, all studies' recall rates still failed to meet the industrial requirements. Detailed investigation of the studies with complete success rates revealed that these works were still developed and studied under limited scope or in the context of specific situations. In other words, they are still far from suitable for industrial usage. For example, the high performance models proposed in past studies could analyze only one type of barcode [16], or the ground truth angles were still manually labeled [46]. Furthermore, when considering the decoding rate, no study could achieve the 100% success target of commercial operations. These findings highlight significant opportunities for improving performance in both detecting and decoding tasks in DL-based barcode recognition.

Although significant progress and successes in applying DL for barcode recognition are evident in several recent studies, various limitations or challenges remain across the barcode analysis domain. These limitations and challenges may be resolved by the continuous improvement of solutions. To identify key opportunities for improvement, in the following subsection, the current challenges or limitations of earlier DL-based barcode recognition studies are presented and discussed.

2) MAJOR CHALLENGES OR LIMITATIONS

Analysis of the reviewed articles highlights two significant challenges in DL-based barcode detection and decoding: data limitations and technical limitations. Discussion of each challenge or limitation generates meaningful insights into barcode analysis in terms of existing achievements, current progress, and improvement opportunities. It is hoped that the information provided below will serve as a valuable guideline for future research.

a: DATA LIMITATIONS

It is undeniable that most challenges associated with DL-based barcode detection are attributable to the data used in the learning process. The critical data challenges found in the current articles have already been discussed in the relevant sections.

Data Annotation: One of the most serious difficulties of deploying DL is the lack of annotated collected data. As stated in [30], current research on DL is affected by dataset limitations and annotation problems in special applications. Similarly, the DL-based approach to barcode detection requires open and annotated datasets. However, data annotation still requires manual labeling, which is labor-intensive. As can be seen in [40], [49], [52], [56], the barcode images contained in some training datasets (i.e., the Dubská M. dataset and self-built datasets) were marked manually since they do not provide the ground truth. Hansen *et al.* (2017) [46] and Xiao and Ming (2019) [7] also performed hand-labeling on several 1D barcodes or QR tags with different rotation angles. In [8], manual labelling had been performed before an online open-source toolbox was applied to label barcode regions. In this case, self-supervised algorithms might minimize annotation efforts by generating datasets and automating the annotation process.

Data Scarcity: Another limiting characteristic of the DL-based approach is data scarcity. The DL-based approach is traditionally big data-driven [24] and always requires a relatively large dataset to generate robust models with generalization capabilities [14]. The DL-based approach can produce high-quality models and accurately identify barcodes when the training and test data are sufficiently abundant. However, it is rare to find publicly available barcode datasets that are adequate in size. Clear evidence is provided in [44], wherein the authors used a miniscule barcode dataset in the experimental setup. The selected dataset rendered their proposed model less stable and inappropriate when applied to many product items in the entire warehouse. Similarly, the mixed barcode dataset proposed by Tian *et al.* (2018) [44] contains only a small portion of PDF417, resulting in an imprecise prediction for both training and testing. To address this problem, future research should focus on more intelligent methods for dataset creation [30]. One could continuously develop and improve transfer learning-based solutions, data augmentation schemes [85], and recursive classification techniques and generate synthetic data [35]. Another possible solution would be to develop DL-based barcode detection techniques to learn from sparse and small barcode datasets.

Ideal Data Conditions: Data-related problems may emerge when datasets are diverse in terms of representative scenarios and ideal conditions. The majority of the acquired barcode image dataset relies on ideal conditions rather than harsh conditions that are characteristic of the practical environment. This may limit the DL process's applicability in the physical world. As seen in [37], the designed CNN architecture in their proposed model did not combine the characteristics and harsh conditions of QR barcodes. Concerning the barcode tags on parcels in inventory or warehouses [44], the training data are simply taken with the same single product from different angles in a rotation platform, whereas testing images are collected from real conditions. Testing data are highly complex, since an image often contains multiple barcode tags against a complex background. Note that more complicated image backgrounds represent the more challenging phase of the barcode detection task. Testing is then performed under real-world scenarios, and images that are severely distorted and occluded [7] lead to unsuccessful barcode decoding.

Hence, it is crucial to consider the harsh reality of barcode images in real-world scenarios both in training and testing. At the same time, more realistic barcode datasets are also necessary.

b: TECHNICAL LIMITATIONS

Learning Tasks: Despite the DL method's successful application to barcode detection and analysis, most of the DL-based architecture used hitherto has been specifically trained to learn and perform only a particular task associated with barcode recognition (detection or decoding). DL-based barcode detection methods cannot simultaneously support multiple barcode analysis tasks (e.g., barcode localization, image processing, and barcode decoding). When considering the application of the DL-based approach, the methods were directly applied for the barcode detection process (positioning or locating separately). DL methods have been proposed in some studies as a means of improving the quality of barcode images prior to decoding (i.e., rotation angle prediction [7] and barcode deblurring [37]). This process is considered one of the image processing tasks. However, no DL-based method was used specifically to obtain barcode information in the decoding-related process. Rather, various barcode decoding tools, such as ZXing, ZBar, and mobile scanner applications, were broadly used to read the barcodes. From this aspect, a single DL model capable of being trained to perform various barcode analysis tasks simultaneously is required. A multi-task learning capacity model of this nature may significantly benefit the DL-based barcode recognition domain.

Classification Ability: Current DL-based barcode recognition approaches largely contribute to the detection of UPC-A and EAN13 barcodes and QR codes. However, at the time of writing, few works have utilized DL methods to detect common barcode patterns that appear on manufactured and real-world items, i.e., Code39, Code93, Code128, ITF, Codebar, DataMatrix, PDF41, Aztec, Codablock, and Maxicode. In [53], the model can only detect one type of barcode. This limitation remains an open problem, and future research should aim to develop a more extensive DL-based method that facilitates simultaneous multi-barcode detection. Although the method proposed by Hansen *et al.* (2017) [46] can detect both 1D and QR barcodes within the same network, the successful decoding rate increases over time. A greater ability to classify more barcode categories is clearly required for DL-based barcode detection. Further comprehensive studies may also be required to prevent misclassification problems when dealing with multi-barcode images with highly complex backgrounds.

Small Barcodes: Many studies have reported the imprecise detection results of DL-based methods when dealing with small barcodes. The findings from [8], [28], and [43] highlighted that most cases of false negatives in barcode detection are due to the small area of barcode images. Smaller barcode objects are sometimes presented with narrower edges that are difficult to detect or are unreadable. The proposed DL model by Yang *et al.* (2019) [8] requires labeling boxes larger than 32*32 pixels, whereas the sizes of some barcode images collected from real data are significantly smaller than expected. Some improvement has been observed, as in [40], which employed an arbitrary quadrilateral for barcode localization; however, the difficulty of detecting very small barcodes persists. Although the DL-based method developed in [47] provides high processing ability for linear distortion barcodes, no favorable impact has been observed for some nonlinear distortion and small 2D barcodes. A simple solution to the small barcode problem would be to enlarge the barcode images. Alternatively, researchers might try the image cropping option to access the central region of the barcode. However, the barcode region should be carefully adjusted. Otherwise, the model's capability could be restricted to predicting large barcode images that occupy almost all image area [44].

Model Extensibility and Robustness: DL-based barcode detection is quite biased when tested exclusively on private resource datasets without benchmarking on other datasets. Evidently, several published studies have used their own datasets, which sometimes are not publicly available. These datasets are of dubious quality, and the barcode data may lack regularization. It is worth emphasizing that different datasets have specificities that impact the learning process. Employing a single dataset may not confirm the model's extensibility and robustness. Although the DL-based method provides high accuracy over self-built data, it is assumed that the methods are not robust enough when applied to other datasets. Future researchers should seek to expand the implementation across different barcode datasets as an extension. The operation may allow the model to yield more precise results in distinctive data environments.

Computational Complexity: Most DL-based barcode recognition methods work with high-quality images that exert high computing demands to ensure high performance. As mentioned in [17], high computing power typically makes it possible to apply the DL-based barcode localization method on the drone for inventory purposes. An experiment from [49] revealed that the training process takes a long time when implemented on the central processor. Compared with other DL-based barcode detection methods and traditional methods, the proposed model by Yang *et al.* (2019) [8] can enhance the decoding success but takes the longest running time. In [37], the proposed DL-based method consumed high computation complexity, rendering the model inapplicable to barcodes in real industrial scenarios. The model compression method adopted in[55] reduces the storage overhead but fails to resolve the computational problem and memory overhead. Thereby, an efficient DL-based method and hardware must be enhanced to ensure a good trade-off between algorithm performance and power consumption.

Detecting and Decoding Performance: As noted in the previous subsection, several DL-based barcode recognition methods have few detectable and decodable barcodes. Typically, the low performance of barcode recognition comes to light when the models are tested on the entire pipeline or under real-life conditions. Low detection or decoding accuracy is caused by numerous technical factors. The first such factor is the employment of coarse localization. For instance, in [29], the focus on coarse localization for barcode detection led the DL method to increase its detection speed while its accuracy deteriorated considerably. An incompatible localization bounding box is another factor that affects the model accuracy. One such work is by the author of [46], wherein the angle prediction network caused the model to decline in accuracy because the bounding box was framed in a large area. In [45], the model showed a relatively low detection rate when detecting barcodes with multiple rotation angles. This was because the ground truth could not cover the bounding box of the particular barcodes precisely. Improvement of model performance thus requires an additional angle and orientation correction process. Another relevant work is [55], wherein the region proposals are horizontal rectangles that cannot precisely fit quadrangular ground truth boxes. The author stated that the localization results of barcode detection should exhibit an arbitrary shape, since the horizontal rectangular bounding boxes are often useless for decoding barcodes.

Flexibility Constraint: Recent DL-based barcode recognition methods are expected to work in real time and automatically [8]. In industry and warehouses, the appearance of existing barcode images attached to products can change over time. DL-based barcode detection should be flexible and updated when the underlying barcode changes or when new barcode images of product items are introduced. However, most of the proposed methods from the articles reviewed have neglected to consider this issue. The proposed DL-based methods are unable to identify previously learned barcodes when adapted to new tasks [12]. To this end, future developers should analyze a range of different approaches in a bid to update neural network models with more data, retraining either update strategies or ensemble update strategies [86].

V. CONCLUSION

Real-time and automatic barcode recognition has attracted attention from both academics and practitioners. To address this complex, modern task, DL is now acknowledged as one of the most effective methods, since it improves on several shortcomings of conventional and recent methods, such as speed, amount of data, and accuracy. Therefore, DL has been widely applied to barcode analysis tasks across several domains in recent years. Nevertheless, to the best of our knowledge, no study to date has systematically reviewed this crucial topic. Regarding the importance of and opportunities for study, we reviewed the latest advances and progress in barcode recognition using DL methods. After reviewing all related articles, we continuously analyzed the information with respect to the specified RQs. Subsequently, several findings of DL-based barcode recognition were identified, and these can be crystallized as eight major challenges, as follows:

- Recently developed DL techniques, which can offer better accuracy and speed, should be adopted to improve the efficiency and effectiveness in barcode recognition performance.
- More real-life conditions of barcode recognition should be inclusively considered and added to the proposed models to increase the possibility of applying DL-based barcode recognition in commercial and real-life situations. Future DL-based barcode recognition for both detection and decoding tasks should be improved to meet actual industrial requirements or real-life usages. It should be boosted to ensure a 100% success rate.
- Public barcode datasets for specific and unexplored domains or situations should be created and provided to facilitate the development and improvement of DL models for barcode recognition.
- The proposed model should be evaluated on more datasets, whether public, private, synthetic, or combinations of different classes. This can generate more opportunities for the proposed model to learn from various barcode images, allowing the model to attain high robustness and high performance.
- To minimize prerequisite processes and prepare new datasets for use, the invented barcode images should be created with greater distinction through the application of different kinds of image transformation operations. This could begin by employing a standard practice of preprocessing and augmentation, as summarized in this paper.
- Concerning data limitations, the development of more realistic barcode datasets with harsh conditions, embedded annotations, and greater size is recommended. These characteristics will help to expand the DL model's applicability in the physical world.
- To uncover technical limitations, the proposed model should be extended with multitask learning capabilities, the ability to deal with different types of barcodes or smaller barcodes, and the ability to update automatically or learn from real-time data. To this end, the extensive DL model for barcode recognition should also be well balanced with respect to resource consumption and model performance.

The above challenges highlight the significant gaps in the existing literature as well as improvement opportunities for future research on deep learning-based barcode recognition. These novel results are expected to support and encourage researchers and practitioners to participate, study, develop, or improve this modern, and crucial topic. Nevertheless, it should be noted that the findings found in this paper still have several limitations relating to the scope of DL, which may have restricted the number of papers selected and reviewed.

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RATAPOL WUDHIKARN received the Doctor of Philosophy degree in knowledge management from Chiang Mai University, Thailand. He is currently an Associate Professor with the Knowledge and Innovation Management Department, College of Arts, Media and Technology, Chiang Mai University. He also works as the Committee of Knowledge and Innovation Management Department, College of Arts, Media and Technology, Chiang Mai University. Recently, he has published academic articles in several well-known international journals, such as the *International Journal of Production Research* (Impact factor 2020 = 8.568), *Journal of Intellectual Capital* (Impact factor 2020 = 7.198), *Management Decision* (Impact factor 2020 = 4.957), and *Asia-Pacific Journal of Operational Research* (Impact factor 2020 = 1.109). His current H-index is seven (SCOPUS). His research interests include intellectual capital (IC), knowledge management (KM), multi-criteria decision making (MCDM), operations research (OR), and total productive maintenance (TPM).

PHASIT CHAROENKWAN received the bachelor's and master's degrees in computer science from Chiang Mai University, Chiang Mai, Thailand, and the Ph.D. degree in bioinformatics from the National Yang Ming Chiao Tung University, Taiwan. He was formally a full-time Lecturer in computer science and digital communications with Mae Fah Luang University and Maejo University, respectively. He is currently an Assistant Professor and a full-time Professor of modern management and information technology with the College of Arts, Media and Technology, Chiang Mai University. Besides, he also worked as a Bioinformatics Researcher in Taiwan. His works are mainly focused on bioinformatics and biomedical informatics especially QSAR. However, he also assists in the use of machine learning approaches for business improvement.

KANOKWAN MALANG received the B.A. degree in modern management and information technology and the M.S. degree in software engineering from Chiang Mai University, Chiang Mai, Thailand, in 2011 and 2015, the master's degree by research certificate under the Erasmus Mundus Program from the Université Lumière Lyon 2, France, and the Ph.D. degree in software engineering from the Beijing Institute of Technology, Beijing, China, in 2020. She is currently a full-time Lecturer at the College of Arts, Media, and Technology, Chiang Mai University. She also works as part of a Research Team at the China Intelligence Center, Chiang Mai University. Her research interests include complex networks, social network analysis, network data mining, and software engineering.