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SURVEY

An Overview of Hand-Drawn Diagram Recognition Methods and Applications

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ABSTRACT Hand-drawn diagrams have been a standard visual communication tool in many disciplines, including architectural design, engineering, and education. The inherent diversity and absence of standardized formats of hand-drawn diagrams make it difficult to recognize them. As a result, there is an increasing need for efficient strategies and approaches for correctly identifying and interpreting hand-drawn diagrams. This research study comprehensively reviews hand-drawn diagram recognition (HDDR) techniques, emphasizing their importance and usefulness in numerous sectors. For the past ten years, articles from the Scopus database on HDDR have been extracted and reviewed. The study explores the approaches, steps, and benchmark datasets available to recognize hand-drawn diagrams. An attempt is made to get insights into the most recent state-of-the-art methodologies, their limits, and potential future advancement directions. This paper also suggests probable solutions to overcome the limitations and develop new techniques for efficiently and robustly recognizing hand-drawn diagrams.

INDEX TERMS Computer vision, deep learning, hand-drawn diagram recognition, machine learning, sketches.

I. INTRODUCTION

From the ancient human era to the recent technologically advanced humans, hand-drawn diagrams and sketches have been the primary means of efficient communication. These diagrams frequently represent intricate ideas, thoughts, and designs, simply and understandably. The hand-drawn diagrams rose from petroglyphs and historical documents to health care, education, business, and recently human-computer interaction, as shown in FIGURE 1.

From the FIGURE 1, it is clear that hand-drawn diagrams have applications in almost every sector. In the healthcare industry, doctors can diagnose Parkinson's disease with the help of spirals or waves drawn by patients. Graphologists use the Wartegg test to determine and deduct anxieties and wishes, emotional states, ambitions, interpersonal interactions, and personal choices. Online tactile maps contain unnecessary information about streets. In contrast, hand-drawn maps have only the necessary details between the source and destination, which is easier for a low vision person to understand and follow. Hence, digitization of such diagrams will automate the detection of Parkinson's disease, determine the mental capability of a person, and help low vision people to walk on streets independently.

Digitization of handwritten diagrams or sketches involved in education, especially distance education, business, and human-computer interaction, will help in the technological advancements of countries. Also, the drawings engaged in criminal investigation and planning of the field operations in the military will speed up the protection of the country from enemies.

Numerous traces of visual communication may still be seen in cave paintings and images, frequently used as comparisons when examining the rise of human development [1].

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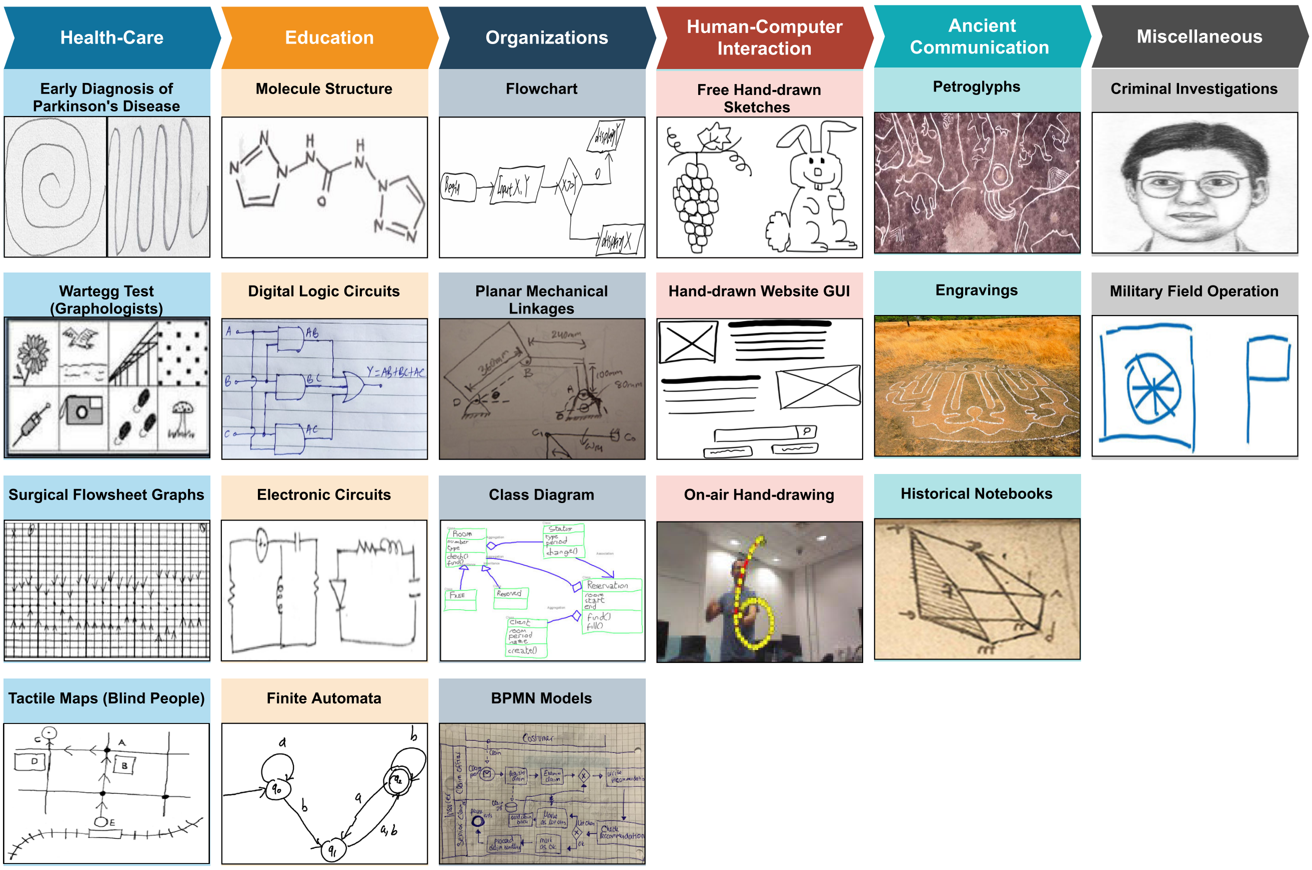

FIGURE 1. Examples and applications of hand-drawn diagrams.

Also, similar petroglyphs are present in different continents as people migrate widely. Hence, if digitized versions of such petroglyphs are available on the cloud, it will be helpful for the archaeologist to understand them efficiently and in less time. Similarly, digitizing handwritten historical documents will save history for generations to come.

The obvious question that comes up is why write by hand and then digitize the contents; the answer to it is handwriting provides good logical benefits [2]. Writing by hand increases the ability to focus on what is written. It improves memory, information organization, and prioritizing skills. Understanding and processing of information is also enhanced through handwriting. The solution to the conceptual question is better for students who write notes by hand than for students who type letters [3].

A. MOTIVATION AND CONTRIBUTION

The motivation behind this manuscript is the need for a review paper on hand-drawn diagram recognition (HDDR). HDDR has many applications, as shown in FIGURE 1, which means many things to be explored and worked on. To work on any HDDR project, a researcher needs information about the approaches that can be used for HDDR, gaps in recent work, benchmark datasets available, challenges, etc. However, the unavailability of such details below one roof motivated us to write this manuscript. The paper's organization is shown in FIGURE 2.

The contributions of this manuscript include

1) Exploration of various applications of HDDR.
2) Detailed overview of approaches and steps used in those approaches for HDDR.
3) Discussion about the benchmark datasets available and results achieved on those datasets so far.
4) Identification of the challenges and future research directions.
5) Suggesting solutions for the challenges.

II. METHODOLOGY

Before conducting the review, it is necessary to define the significance of the work and formulate the research questions. Once the questions are prepared, the next step is to query the relevant articles from the Scopus database. To avoid ambiguity, only one database is used for article selection.

A. SIGNIFICANCE AND GOALS

Though handwriting and hand-drawn diagrams have various advantages, hand-drawn diagram recognition (HDDR) is challenging for computers [4]. Complexities in the chart, such as the inclusion of text into symbols, the flexibility

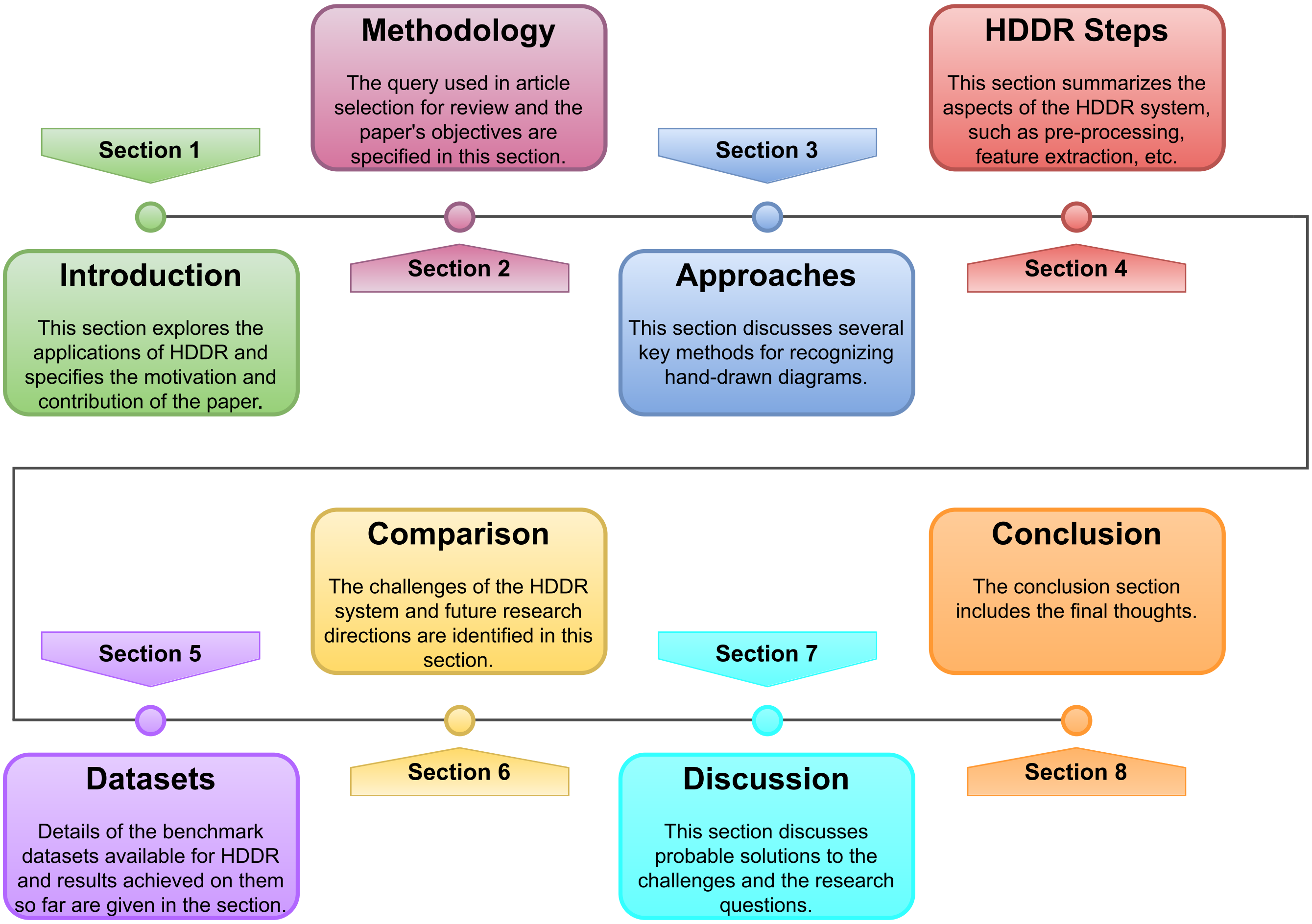

FIGURE 2. Formation of the sections of this paper.

of grammar, symbol extension in any direction, the higher scope of a diagram, etc., make the HDDR difficult. In 1996, Blostein [5] specified six stages for HDDR: pre-processing, segmentation, recognition, spatial relation identification, logical relation identification, and semantic interpretation. There have been efforts to digitize and recognize the essential hand-drawn diagrams in many fields for further modification and analysis using these stages. Research on hand-drawn diagram recognition systems was ongoing, and several strategies were implemented to overcome this difficult challenge.

This research aims to identify the applications where HDDR can be applicable, to find out the gaps in the work done on HDDR, and to determine the approaches and techniques used for HDDR. Most importantly, it determines the challenges faced and defines future research directions to be worked on. These goals are formulated into research questions as shown in TABLE 1.

B. RESEARCH APPROACH

The search focuses on the fundamental ideas pertinent to this overview's purpose. Thousands of articles are available on handwriting recognition, but this manuscript focuses on recognizing hand-drawn diagrams or sketches. Hence the query used on Scopus database for the search is: (TITLE ("hand-draw*" OR "hand draw*" OR "handdraw*" OR "hand-sket*" OR "hand sket*" OR "handsket*") AND TITLE ("recogni*")) AND PUBYEAR > 2012 AND PUBYEAR < 2024 AND (LIMIT-TO (LANGUAGE, "English")).

The focus was on the work done for HDDR in the last ten years. The query yielded 50 articles, so the review is based on those articles for answering the research questions.

TABLE 1. Research questions defined for the work.

Sr. No.	Research Question
RQ1	Which approaches have been used for HDDR?
RQ2	What are the steps followed by those approaches for HDDR?
RQ3	Which datasets are available, and what parameters are used to evaluate the performance of those datasets?
RQ4	What are the challenges and unresolved problems in HDDR?

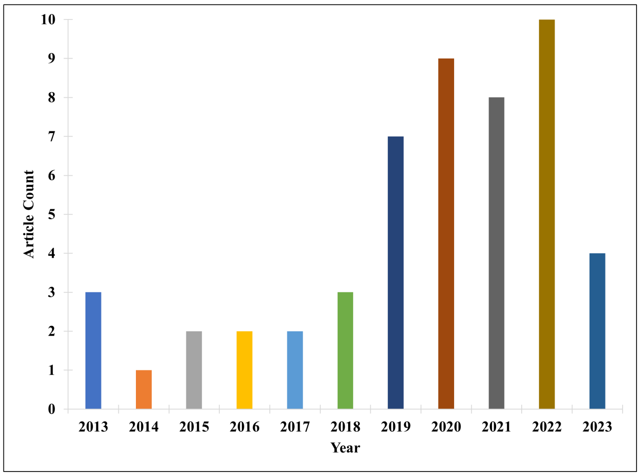

FIGURE 3. Year-wise distribution of the selected articles.

FIGURE 4. Keywords associated with the selected articles.

The year-wise count of the published articles over the previous ten years is depicted in FIGURE 3. From the figure, an increase in the number of articles in recent years can be observed.

Keywords are the most important aspect to find the relevance of the articles. Indexed keywords of the selected papers are shown in FIGURE 4. The size of the keyword indicates its co-occurrence. The co-occurrence analysis of the keywords will help answer RQ1, i.e., finding the different approaches and applications of the HDDR.

The articles were synthesized to answer research questions 2, 3, and 4. The synthesis results are discussed briefly in the following sections, followed by the probable solutions.

III. APPROACHES FOR HDDR

Work on HDDR systems was ongoing, and several strategies were implemented to overcome this difficult challenge. The first step of the review process was to find out the various approaches used for HDDR. The techniques are shown in FIGURE 5. The figure shows the advancement in the methods from template matching, graph theory, and segmentation to machine learning and deep learning. The overview of such techniques for recognizing hand-drawn diagrams, along with the referenced articles, are discussed in this section.

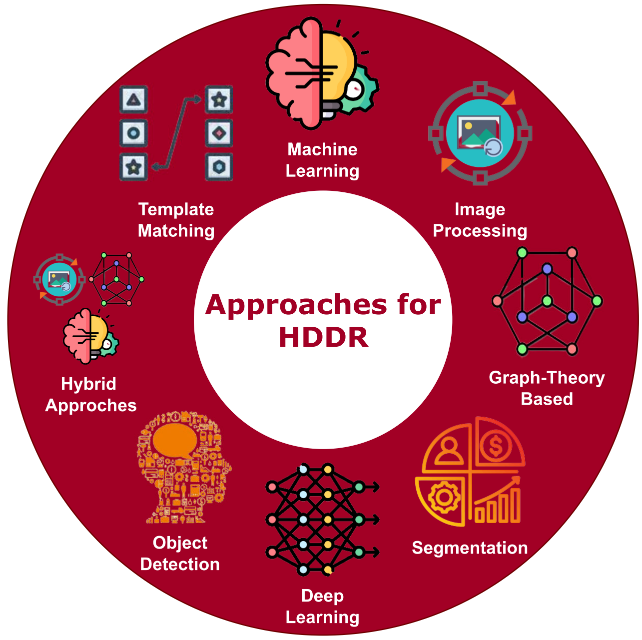

FIGURE 5. Approaches used for HDDR in the reviewed articles.

1) **Image Processing Techniques:** Hand-drawn diagrams have been recognized using conventional image processing techniques like edge detection, contour analysis, and region segmentation [6]. Due to differences in stroke thickness and quality, these techniques may not be as effective for complex drawings as for simple symbols and diagrams.
2) **Template Matching:** To identify the best match, template matching entails comparing hand-drawn symbols with predetermined templates [7]. While this method can successfully handle straightforward diagrams, it has limitations when dealing with more intricate and abstract graphics.
3) **Graph Theory-based Approaches:** Graph theory is sometimes used to represent hand-drawn graphics as graphs. The graph's nodes represent the diagram's elements, while the edges show their connections. Recognition entails comparing the sketched diagram's subdivisions to predetermined templates [8], [9].
4) **Machine Learning:** Support vector machines (SVMs) and k-nearest neighbors (kNN) are examples of machine learning methods with supervision that may be trained to perform classification tasks in HDDR [1], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20], [21], [22], [23].
5) **Deep Learning:** Since the invention of deep learning, several methods have been used to recognize hand-drawn diagrams [7], [11], [13], [19], [24], [25], [26], [27], [28], [29], [30], [31], [32], [33], [34], [35], [36], [37], [38], [39], [40], [41], [42], [43].

a) **Convolutional Neural Networks (CNNs):** In recognizing hand-drawn symbols and diagrams, CNNs have demonstrated encouraging results. CNNs may learn to recognize intricate patterns and structures by receiving training on huge datasets of labeled diagrams.
b) **Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) Networks:** For jobs requiring sequence recognition, such as figuring out the sequence in which a diagram's strokes were drawn, RNNs and LSTMs are employed.
c) **Graph Neural Networks (GNNs):** GNNs can efficiently use structural information since they can operate directly on network illustrations of diagrams.

6) **Combination of Object Detection and Semantic Segmentation:** Some current methods label the pixels that belong to the different elements in the diagram using semantic segmentation and object detection to recognize the specific components in the diagram. The combination enables more precise recognition of intricate diagrams [10], [27], [35], [39], [44].
7) **Hybrid Approaches:** To produce hybrid recognition systems, some solutions integrate artificial intelligence algorithms with methods for image processing [38], [40].

IV. STEPS OF HDDR SYSTEM

The steps of the HDDR system are shown in FIGURE 6. Initially, input is provided to the system. The information can be a diagram captured through a scanner if drawn through pen on paper (offline mode), or a direct image (online mode) is provided if drawn through a stylus or mouse.

Sometimes, the whole document is given as input in such a case diagram needs to be identified from the document. The next step is to capture the diagram from the document given as input. Various methods have been proposed to separate the diagram from the paper, known as mode detection or text/non-text classification methods. The mode detection method determines whether a user produces handwritten text, equation, or symbol. The captured diagram undergoes various steps of HDDR, such as pre-processing, segmentation, feature extraction, classification, and recognition. The output of the HDDR system is the diagram converted to digital form. This section explores the methods used in various steps of the HDDR system.

A. PRE-PROCESSING METHODS

Numerous computer vision and image analysis work needs the use of pre-processing methods. These are applied to improve image quality, eliminate noise, and prepare the data for further analysis. The following are pre-processing methods used in HDDR systems.

1) **Resizing:** An image can be easier to manage and computationally less difficult by being resized. It can also aid in uniformizing the image size for deep learning algorithms [13], [14], [25], [40].
2) **Normalization:** When pixel values are scaled to a standard range, such as [0, 1] or [-1, 1], it is possible to make sure that the illumination levels of various images are comparable [1], [9], [21], [24], [43].
3) **Grayscale conversion:** Grayscale conversion of an image can streamline processing while preserving crucial structural data. It is frequently employed when color data is not necessary.
4) **Noise Reduction:** With the help of the Gaussian filter, high-frequency noise is reduced, and it also smoothens the image [6]. Salt-and-pepper noise can be eliminated by substituting the value of every pixel with the average value in its neighborhood. More sophisticated denoising methods, such as the Non-Local Means (NLM) filter or wavelet denoising, can also reduce noise [23].
5) **Image Binarization:** Sets a threshold to divide a picture into binary areas. It is frequently used in the task of segmenting images [1], [14], [20], [22], [23], [25], [30], [43], [45], [46].
6) **Data Augmentation:** The robustness of the predictions can be increased by supplementing the input data for training using modifications of hand-drawn diagrams, such as various styles, layouts, and amounts of noise [31], [36], [41].

Other methods used for pre-processing in combination with the above techniques are degradation of image [31], node selection [9], and simplified conversion from raw image [18], [19]. The precise objectives of the image analysis work and the qualities of the input information determine which preprocessing methods should be used.

B. SEGMENTATION TECHNIQUES

A crucial problem in computer vision is image segmentation, which involves dividing the image into significant components or parts. These parts in the image relate to specific objects or exciting areas. Outlined are a few typical segmentation strategies:

1) **Density-Based Spatial Clustering of Applications with Noise (DBSCAN):** DBSCAN is resistant to object morphology and distance changes because it can detect densely packed areas in the feature vector. Even while DBSCAN can be used for picture segmentation, it's important to remember that it focuses largely on spatial density. It could not work well when objects have comparable volumes but varied morphological properties. In these circumstances, integrating DBSCAN with additional methods, including feature-based grouping or neural network-based approaches, may produce superior segmentation outcomes [44].

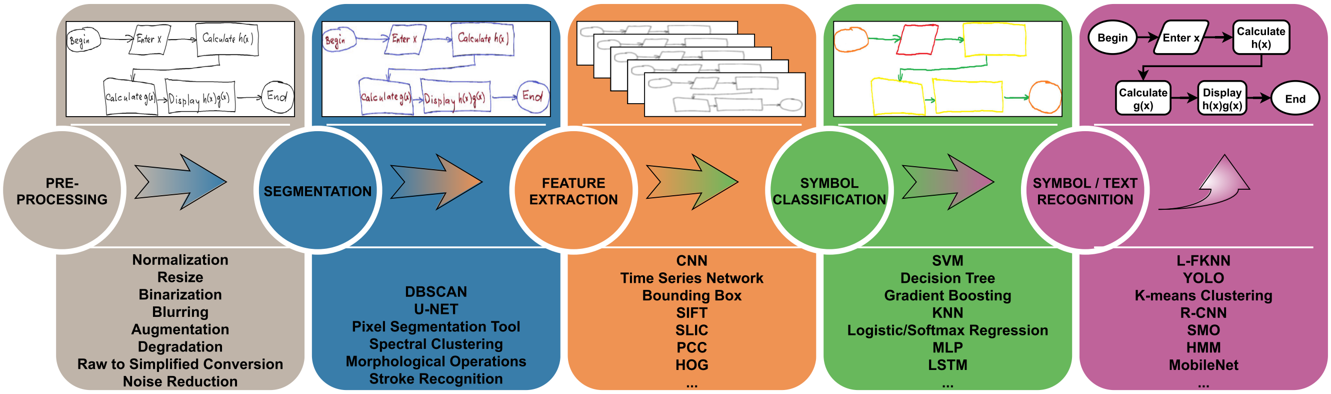

FIGURE 6. Workflow of diagram recognition system.

2) **U-Net:** For the segmentation of images, the U-Net framework is a well-liked and very successful CNN design. The symmetric and skip-connection nature of the U-Net architecture makes it possible for it to collect simultaneously high-level semantic data as well as excellent data in the segmented sections. A labeled collection of input images and matching segmentation masks are commonly used to train a U-Net model. Because there are previously trained U-Net algorithms accessible, applying transfer learning to particular segmentation tasks is made simpler [7].
3) **Pixel Segmentation Tool:** For diverse picture segmentation problems, numerous image segmentation programs are available, both for conventional computer vision and deep learning-based techniques. A few well-known tools for image segmentation are Open Source Computer Vision Library, Scikit-Image, Dlib, SimpleCV, Deep Learning Frameworks, Labelbox, Supervisely, etc. The selected tool will rely upon the segmentation task's particular needs and difficulty level [17].
4) **Spectral Clustering:** It can capture complicated cluster structures and consider the overall data structure, making it appropriate for picture segmentation when objects have shape variations and differ in size and luminance. Unlike conventional techniques like K-means, spectral clustering does not presuppose whether clusters are convex or spherical. When used properly, spectral clustering is an adaptable method that can produce precise and reliable outcomes for image segmentation tasks, particularly when working with difficult images with complicated structures and different item forms [1].
5) **Morphological Operations:** Morphological operations are performed on the binary images. The erosion and dilation are done to change the appearance of the image. To remove noise, erosion is applied, followed by dilation and filling up the gaps present in the image done by dilation followed by erosion [20].
6) **Stroke Recognition:** Learning images' layout and subject matter may be understood by identifying and analyzing strokes. Sometimes, it can be used as a pre-processing step when the strokes are crucial for expressing information. This is because it can increase the precision of item or region delineation [46].

Specific attributes of the images, plus the application's objectives, determine the segmentation approach to use. Combining methods or employing a tailored methodology is frequently necessary to obtain the required segmentation precision and robustness.

C. FEATURE EXTRACTION TECHNIQUES

In HDDR, the objective is to extract relevant features to comprehend the content and layout of images. These characteristics are essential for interpreting and conducting further investigation. The following feature extraction methods are frequently applied to the HDDR.

1) **Stroke Analysis:** Individual strokes are frequently used to create hand-drawn diagrams. It can be useful to extract features at the stroke level. Characteristics may include the thickness, direction, and intensity of the strokes [46].
2) **Graph-based Representations:** Draw the image as a graph, with the forms and strokes acting as nodes and the connections as edges. Node degree, prominence ratings, and graph patterns are examples of graph-based attributes [8], [9].
3) **Shape Descriptors:** Extraction of shape-related properties from recognized or split image objects. Characteristics including dimension, region, boundaries, and tightness can characterize shapes [10], [27], [36].
4) **Contour Analysis:** Extraction of contour-related characteristics for objects. Contour size, contour curve, and Fourier classifiers are examples of features [29].
5) **Skeletonization:** Skeletonization approaches simplify visualizations of complicated shapes. Examples of skeleton traits are branch points, termination points, and size [1].

6) **Scale-Invariant Features:** Extracting scale-invariant characteristics can be helpful if diagrams have different scales and orientations. Scale-invariant feature transform (SIFT) and speeded-up robust features (SURF) can be used [6].
7) **Deep Learning-based Features:** CNN layers may be employed to learn features, which can be applied to recognition [13], [24], [27], [30], [40], [41].
8) **Histogram of Oriented Gradients (HOG):** HOG can be used to record the image's gradients and boundary characteristics. It is beneficial for identifying specific diagrammatic objects or forms [14], [15], [20], [22], [47].
9) **Local Binary Patterns (LBP):** LBP represents the local textures in the image. It is useful in recognition through textures [15].

These methods can be combined to capture various characteristics of the images, giving a comprehensive feature representation for training and recognition. Additionally, for HDDR, deep learning algorithms, such as CNNs and recurrent neural networks (RNNs), have become more prominent.

D. CLASSIFICATION TECHNIQUES

The categorization of handmade drawings into distinct groups or classes is a component of HDDR. Different classification algorithms might be used to resolve this issue depending on the intricacy of the sketches and the data at hand. The below-mentioned categorization methods are frequently employed in HDDR.

1) **Traditional Machine Learning Algorithms:** SVMs can classify diagrams into binary or many categories by acquiring the decision boundaries that identify the various classes [1], [9], [13], [14], [19], [20], [21], [22], [23].
   Ensemble learning techniques can deal with complicated and multidimensional spaces of features, including random forests [14], [18], [19], [48].
   Diagrams are classified using K-NN based on the nearest neighbors' feature spaces [14].
   For text-based classification problems in images, naive Bayes classifiers are efficient.
2) **Deep Learning:** CNNs are pretty good at recognizing diagrams from images. They can learn hierarchical characteristics from the input photos immediately [25], [42], [49].
   If the layout and placement of diagrammatic elements are crucial, as they often are in flowcharts and sequential diagrams, RNNs can be used [19].
   When performing tasks that call for a combination of spatial and linear reasoning, CRNNs combine the best aspects of CNNs and RNNs.
3) **Transfer Learning:** Transfer learning approaches start HDDR tasks by leveraging pre-trained models often trained on massive datasets. The model can be fine-tuned to suit the particular purpose [41].
4) **Ensemble Methods:** The outcomes of several basic classifiers can be combined using ensemble techniques like bagging and boosting, which enhance classification performance overall [14].
5) **Graph-Based Classification:** Graph convolutional networks (GCNs) may capture connections and properties within a graph's framework for diagrams represented as graphs.

Other classification techniques used are softmax regression [40], euclidean distance [17], multi-layer perceptron [21], etc. The type of diagrams, the accessibility of labeled data, and the particular needs of the identification task are just a few of the variables that influence the classification technique selection. The best method for a specific HDDR challenge is frequently determined by testing and analyzing a representative dataset.

V. BENCHMARK DATASETS

Using benchmark datasets makes it easier to check the models' performance and compare various algorithms or methods. This section details the benchmark datasets for recognizing flowcharts, finite automata, sketches, etc.

A. ONLINE FLOWCHART DATABASE (FC_B) [50]

It is a database of online sketched flowcharts. Twenty-four users drew 28 diagrams, leading to 672 diagrams on the Lenovo X61 tablet. The standard used for data storage is InkML. The stroke information is also stored in the database. The database also contains text blocks and arrow information stored as connectors, heads, and shafts. The database includes a training dataset designed by ten users containing 280 diagrams, a validation dataset by seven users containing 196 diagrams, and a test dataset containing 196 diagrams. The database can be downloaded from link https://cmp.felk.cvut.cz/b̃ reslmar/flowcharts/index.html.

B. ONLINE FINITE AUTOMATA DOMAIN DIAGRAM DATABASE (FA) [51]

The database contains an online sketched diagram of the finite automata domain. Twenty-five users drew 12 diagrams, leading to 300 diagrams on the Lenovo X61 tablet. The standard used for data storage is InkML. The pen tip, time, and pressure information are also stored in the InkML file. The database provides annotation of the arrowhead and shaft. The database contains a training dataset designed by 11 users containing 132 diagrams, a validation dataset by seven users containing 84 diagrams, and a test dataset by seven users having 84. The database can be downloaded from link https://cmp.felk.cvut.cz/ breslmar/finite_automata.

C. ONLINE FLOWCHART DATABASE (FC_A) [52]

Thirty-five writers drew 419 handwritten flowcharts. The database is stored in InkML format. The training set contains 248 samples with 14 different patterns. The test set includes 171 examples with 14 other various designs. The database is created using an Anoto pen. In the database, the groundtruth of each flowchart is also mentioned, which helps detect correct stroke labels, segmentation, and recognition. The database can be downloaded from http://tc11.cvc.uab.es/datasets/OHFCD_1.

D. TECHNICLE UNIVERSITY BERLIN DATABASE (TU-BERLIN DATASET) [53]

One thousand three hundred fifty amateur sketch artists participated in an event sponsored by Amazon Mechanical Turk (AMT) to generate the dataset. This dataset has 250 object types and 20,000 overall sketches. There are 80 sketch elements in each group of objects. Each image is of size 1111 by 1111. For this sketch, human recognition accuracy is 73.1%. The database can be downloaded from https://cybertron.cg.tu-berlin.de/eitz/projects/clas sifysketch/.

The other sketch datasets available are as follows. The course of Action Diagrams (COAD) [54] is a selected group of hundreds of images used for field action planning by the US military. There are 20 categories, and while some symbols have unique shapes, others only exist as a portion of a handful of symbols.

Each of the 75,472 photos contains 12,500 hand-drawn or sketched items, and are 125 classes assigned to each image in the Sketchy dataset [55].

The SHREC13 dataset [56] contains just one stroke sketch image. There are 2800 drawings in this collection, which are divided into 90 classes.

E. NicIcon DATABASE [57]

NicIcon database contains symbols of multistroke. It includes 25,000+ characters divided into 14 classes. The database contains the training dataset, validation dataset, and test dataset. It includes both online and offline datasets. The database can be downloaded from link http://unipen.nici.ru.nl /NicIcon.

F. DECIMER DATASET [58]

Twenty-four volunteers from the Westphalian University of Applied Sciences, Germany, contributed their free time to the generation of the DECIMER dataset. It includes 5088 PNG pictures of distinctively hand-drawn chemical structural representations. The collection comprises stereochemical information, charged groups, and various isotope kinds. It contains online (sketched on a smart device and saved) and offline (drawn on white paper and captured) samples. The database can be downloaded from the link: https://zenodo.org/record/6456306.

G. HandPD DATASET [59]

The HandPD dataset includes handwritten tests from the Healthy Group and the Patient Group, which comprises people with Parkinson's disease (PD). The primary assignment is filling up a form of four spirals and four meanders, cutting it out, and saving it as a "jpg" image. The dataset includes 92 participants, of which 18 are healthy and 74 are ill. The total dataset comprises 736 photos divided into two groups: the healthy group, which consists of 72 images, and the patient group, which consists of 296 photographs. The collection includes 368 images from each drawing, such as spirals and meanders. The database can be downloaded from the link: https://wwwp.fc.unesp.br/ papa/pub/datasets/ Handpd/.

From the survey, the results achieved on benchmark datasets are collected and shown in TABLE 2.

TABLE 2. Brief of benchmark databases and results.

Author	Year	Dataset	Result (%)
Ali, S. et al. [24]	2023	TU-Berlin	Accuracy: 95.05
Li, Z. et al. [25]	2022	HandPD	Accuracy: 85.70
Fang, J. et al. [27]	2022	FC-A, FC-B, FA	Accuracy:70.8,80.9,85.0
Zhang, L. [29]	2021	COAD	Recognition rate 73.24
M. Thangakrishnan and K. Ramar [13]	2021	Sketch, SHREC13, Flickr 15k, Sketchy, TU-Berlin	Mean Average Precision (MAP) 58.9, 41.2, 29.9, 46.7, 34.5
Ji, Q. [32]	2021	TU-Berlin	MAP 71.80
Schafer, B. et al. [36]	2021	hdBPMN	Recognition rate Shape 95.7, Edge 91.8
Ferdib-Al-Islam, Akter, L. [14]	2020	Parkinson's Drawings	Accuracy wave 86.67, spiral 89.33
Pan, C. et al. [38]	2020	COAD, Omniglot	Accuracy:82.31, 84.75
Gupta, M. et al. [18]	2019	Quick draw	Accuracy 82.34
Gupta, M., Mehndiratta, P. [19]	2019	Quick draw	Accuracy 82
Altun, O., Nooruldeen, O. [1]	2019	FC_B, FA	Accuracy 95.87, 94.99
Hayat, S. et al. [41]	2019	TU-Berlin	Accuracy 94.57
Dey, S. et al. [42]	2018	NicIcon	Accuracy 97.01
Eicholtz, M., Kara, L.B. [22]	2015	MECH135	mAP 87

VI. CHALLENGES AND FUTURE RESEARCH DIRECTIONS

The challenges in hand-drawn diagram recognition include

1) **Ambiguity:** Hand-drawn diagrams frequently have arbitrary borders and overlapped parts, which makes them difficult to recognize.
2) **Variability:** Different drawing styles, stroke weights, and other visual characteristics result from individual differences in how diagrams are created, making identification more difficult.

3) **Scale:** Diagrams can range greatly in size from quick drawings to intricate, precise representations; therefore, they must be adaptable to many scales.

The reviewed articles also faced other challenges, which can be used as a future research direction for upcoming researchers. Such challenges are discussed in TABLE 3. It cannot be easy to distinguish distinct drawing styles, mainly when working with diagrams created by many people. Partially drawn or ambiguous elements are complex for the system to recognize and understand since it has to guess the intended meaning from incomplete visual signals. Automated systems may find it challenging to distinguish between some symbols because they can overlap or appear unusually. It is difficult to understand relationships between components and derive significant connections, mainly when working with intricate designs. Hand-drawn diagrams frequently have noise, distortions, or inadvertent anomalies. Systems for recognition ought to be able to adjust to novel symbols and contexts without requiring a lot of retraining. Accurate recognition depends on knowing each element's function and how it fits into the diagram's overall purpose. Reaching quick and processing speeds is crucial for applications that need real-time recognition. There can not be enough standardized datasets for evaluation, and the annotation process could be laborious and subjective.

A multidisciplinary strategy combining machine learning, image recognition, and interaction between humans and computers principles is needed to address these issues.

VII. DISCUSSION

The various approaches (RQ1), steps (RQ2), and benchmark datasets (RQ3) available according to the reviewed articles are discussed in sections III, IV, and V. Still, there are various challenges and massive scope for future researchers (RQ4), as mentioned in section VI. This section discusses the probable solutions for each research question.

A. RQ1

With recent technological advancements, the approaches that can be used to improve the performance of HDDR systems are as follows.

Attention Mechanisms: To improve recognition performance and handle large-scale diagrams more successfully, attention mechanisms have been incorporated into recognition models to help users concentrate on the most critical areas of the diagram.

Natural Language Processing (NLP): When hand-drawn diagrams have text messages, natural language processing (NLP) methods can be utilized to identify the text, analyze it, and give the chart a more profound significance. NLP approaches may obtain text-based features when the image has textual annotations.

Human-in-the-Loop: To recognize complicated or contradictory hand-drawn designs, human interaction or aid may occasionally be needed. Users may participate in the recognition process through interactive systems.

Domain-Specific Models: Domain-specific algorithms and procedures can be created to increase recognition precision for specific categories like circuit diagrams, flowcharts, or architectural designs.

B. RQ2

Various methods can be used at multiple steps of HDDR to improve the performance.

1) PRE-PROCESSING

Contrast enhancement techniques can be used by shifting the pixel's intensity values to increase an image's local contrast.

Edge detection techniques such as Sobel, Prewitt, and Canny can draw attention to feature extraction techniques towards the edges and gradients.

Positioning a visual or cutting it to isolate a particular area of interest can enhance later processing stages.

2) FEATURE EXTRACTION

Corner Detection: It can be helpful to note important junctions or corners on the sketch. It is possible to extract corner characteristics like Harris or Shi-Tomasi corners.

Texture and Color Analysis: Texture and color properties might offer helpful information for colored diagrams. Local binary structures or coexistence matrices, which are texture features, can be used to define the texture of various locations. Color characteristics like color histograms or color moments can capture color distributions.

3) CLASSIFICATION

One-Class Classification: One-class classification, wherein the objective is to find diagrams of a particular class while classifying every other class as outliers or anomalies, may, in some circumstances, be more practical.

Clustering Followed by Classification: Similar diagrams can be grouped using clustering methods like K-means, and each cluster can have its classification algorithm applied.

Active Learning and Semi-Supervised Learning: These approaches can effectively utilize the annotated data already available and lessen the requirement for significant labeling in situations with little labeled data.

Fusion of Multiple Modalities: Diagrams can be classified using multimodal techniques that combine visual and textual elements.

C. RQ3

Benchmark datasets are available only for a few applications, such as Parkinson's disease in health care, molecule structure and finite automata in education, flowcharts in organization, and miscellaneous sketches. Still, there is a need to create datasets for other applications such as electric circuits, Lewis structures, etc.

The biggest challenge in the creation of a dataset is annotation or labeling. The first option is to label

TABLE 3. An overview of the reviewed HDDR techniques with the future research ideas.

Author(et al.)	Advantages	Challenges/Future Work	Diagram Type
Zaki, M. H. [60]	The proposed software can extract diagrams from scanned images, format them, and recognize them.	Other engineering schematics must be taken into account.	UML
Hou, X. [26]	They added spatial and channel attention techniques within the feature extraction system to emphasize more distinct feature representations and improve its potent sketch recognition performance.	Work on developing an automatic recognition system should be upgraded.	Sketches
Rachala, R. R. [10]	Rebuilding a hand-drawn electrical circuit using image analysis and object identification methods is fully addressed.	A large dataset with more major variants will be required to attempt to construct a complete deep-learning technique.	Electronic circuits
Pavithra, S. [6]	The outcome is anticipated even when the input drawing is produced in various ways.	It can be incorporated with numerous internet platforms by being developed as a tool.	Electronic circuits
Adhikari, J. [11]	Give consumers access to a smartphone app that uses virtual reality to let them see the detected molecule in 3-D space.	Have to create a database of manually drawn Lewis structures	Molecule Structure
Wrobel, K. [12]	The proposed approach applies to Parkinson's disease tests for screening.	Need to carry out studies with multiple classifications for various tremor illnesses.	Spiral
Xu, Y. [44]	Their approach links a series of manually drawn images of a single object and a task requiring the detection of several objects.	Several worthwhile study areas include color production for sketch images, identifying the structure of hand-drawn graphite drawings, converting pixel-format drawings into vector-format pictures, and developing new techniques to enhance segmentation methods.	Wartegg Hand-drawings
Keerthi Priya, A. [28]	Instead of choosing where to place the symbols and designing the diagram, an intuitive graphical user interface is offered for drawing circuit symbols.	Need to create a benchmark database of manually drawn circuits.	Electronic circuits
Dey, M. [30]	They attempted to automate the process of HDDR by first identifying the manually drawn circuit elements.	A notable flaw in the suggested framework is that it's unable to effectively distinguish between highly similar elements, such as ammeter and voltmeter, which is thought to be decreased by including novel strategies that more precisely reflect the local features.	Electrical and Electronic circuits
Weir, H. [31]	The proposed equipment might be easily implemented into labs and classrooms to spur advancements in education and research.	The variety in manually drawn styles of fonts and symbol placement is a considerable challenge in identifying molecules.	Hydrocarbon structures
Berari, R. [35]	The findings show a desire to use object detection methods to bridge the gap between an internet site's appearance and its software.	For developers passionate about resolving artificial intelligence difficulties, there is a need to produce a more difficult webpage UI database through a technological object identification perspective.	Webpages UI
Adorno, W. [7]	Every healthcare organization or nation still needs to establish a method for digitizing the information obtained through the surgical flowsheets can benefit from this research.	The post-processing techniques might be modified and more rigorous to extract data from the segmentation masks more precisely.	Surgical flowsheet graphs
Deufemia, V. [8]	Their proposed method could be applied to collaborative drawing identification that utilizes the decoding of digital ink strokes and offline drawing identification relying upon the image processing of the scanned document.	Engineering symbols with intricate patterns may be identified using more flexible approaches.	UML class diagrams
Fichou, D. [39]	They demonstrated the possibilities that may be unlocked by merging machine learning with user interfaces.	Real-world scenarios assume relative positioning plus a structure of many element types.	Webpages UI
Polančič, G. [16]	The recognition of manually drawn method schematic components with different degrees of precision is made possible using solution-based and trained TensorFlow models.	Need to produce and look for more manually drawn BPMN elements to enhance the model performance.	BPMN models
Wang, H. [40]	This approach has great recognition precision in addition to some rotation invariance.	Implementing a robust approach for recognizing hand-drawn circuits is a need of the day.	Electronic circuits
Huoming, Z. [17]	KNN is used to segment and identify the intended diagram based on its pixel distribution properties.	The drawbacks include the high mathematical difficulty and elevated spatial complexity of KNN.	Electrical circuits
Alwaely, B. [9]	The identification system is resilient to many sketching and writing alterations through its quick instantaneous operation and uniformity to rotation and flips.	The suggested model can be improved so that deaf people can use it.	In-Air number and shape
Aruleba, K. [47]	The study provides a successful offline method to handle manually drawn finite automata, emphasizing pre-processing and feature extraction.	Need to generate a framework keeping performance high while minimizing the computational complexity	Finite automata
Moetesum, M. [20]	A variety of morphological operations are used for segmentation, and HOG descriptors and SVM classifiers are used for recognition.	It could involve more intricate circuit designs and electronic and digital parts.	Electronic circuits
Hsiao, S.-J. [61]	This research established a real-time, online communication technique for identifying network trends on the World Wide Web.	The suggested identification method can be improved for Internet shopping and e-commerce.	Sketches (Patterns)
Szwoch, W., Mucha, M. [46]	It adheres to modern trends for creating software powered by intelligent technologies that actively engage users in conversation.	The future work can integrate the proposed framework and create a system for the automatic production of source code.	Flowchart

the symbols using an open-source tool such as Label Studio. Another option is to develop or use methods to work on unlabeled data, such as unsupervised learning techniques.

It's vital to remember that hand-drawn diagram identification is still developing, and which technique to choose relies on the application's particular needs. To increase the precision and usefulness of HDDR systems, researchers and programmers keep looking into novel approaches and refining existing ones.

D. RQ4

Innovative approaches are needed to address the problems with hand-drawn diagram recognition, and these approaches frequently combine machine learning, image recognition, and human-machine interaction methods.

To make models more tolerant of various drawing styles, researchers can employ deep learning models, augment data for training with variances in drawing styles, and investigate domain adaptation strategies. Researchers can make unclear aspects more understandable using interactive interfaces, incorporating contextual information, using probabilistic models, and permitting user interactions.

Graph-based approaches and attention mechanisms can be utilized for symbol segmentation and recognition. Geometric limitations can be included to improve the diagram's spatial comprehension. Reliable, less noise-sensitive feature extraction techniques can be examined. It is possible to create modular architectures that quickly integrate new symbols and adjust to various domains.

Transfer learning methods can use the knowledge from models previously trained in fresh symbol recognition tasks. By using explainable AI techniques, individuals can verify the machine's interpretations and get insight into making decisions.

Creating self-supervised or semi-supervised learning strategies can lessen reliance on thoroughly annotated datasets. Crowdsourcing techniques can also be investigated for data annotation to ensure a diversity of opinions during the labeling process.

Putting these concepts into practice can help build more reliable and flexible HDDR systems. Furthermore, working together, researchers, practitioners, and users might yield insightful solutions to particular problems in real-world applications.

VIII. CONCLUSION

Recognition of hand-drawn diagrams is essential and crucial, as it has applications in almost every field. This paper comprehensively reviews articles on HDDR from the Scopus database. The study is partitioned into four research questions: approaches, steps, datasets, and challenges of HDDR. The most commonly used methods for HDDR are machine learning and deep learning. Image binarization and normalization are preferred to pre-process the diagrams and prepare for further steps. Features are extracted mainly using CNN and HOG as they improve the performance of the methods. Machine learning algorithms such as SVM are most preferred for classifying the symbols in the diagrams. For recognition, deep learning algorithms are selected. Furthermore, the probable solutions for the challenges and future research directions are also presented. The study will help researchers to find novel solutions to HDDR.

REFERENCES

[1] O. Altun and O. Nooruldeen, "SKETRACK: Stroke-based recognition of online hand-drawn sketches of arrow-connected diagrams and digital logic circuit diagrams," *Sci. Program.*, vol. 2019, pp. 1–17, Nov. 2019.

[2] M. A. P. Alonso, "Metacognition and sensorimotor components underlying the process of handwriting and keyboarding and their impact on learning. An analysis from the perspective of embodied psychology," *Proc.-Social Behav. Sci.*, vol. 176, pp. 263–269, Feb. 2015.

[3] P. A. Mueller and D. M. Oppenheimer, "The pen is mightier than the keyboard: Advantages of longhand over laptop note taking," *Psychol. Sci.*, vol. 25, no. 6, pp. 1159–1168, 2014.

[4] R. Davis, "Magic paper: Sketch-understanding research," *Computer*, vol. 40, no. 9, pp. 34–41, Sep. 2007.

[5] D. Blostein, "General diagram-recognition methodologies," in *Proc. Int. Workshop Graph. Recognit.*, 1995, pp. 106–122.

[6] S. Pavithra, N. K. Shreyashwini, H. S. Bhavana, G. Nikhitha, and T. Kavitha, "Hand-drawn electronic component recognition using ORB," *Proc. Comput. Sci.*, vol. 218, pp. 504–513, Jan. 2023.

[7] W. Adorno, A. Yi, M. Durieux, and D. Brown, "Hand-drawn symbol recognition of surgical flowsheet graphs with deep image segmentation," in *Proc. IEEE 20th Int. Conf. Bioinf. Bioeng. (BIBE)*, Oct. 2020, pp. 295–302.

[8] V. Deufemia and M. Risi, "Multi-domain recognition of hand-drawn diagrams using hierarchical parsing," *Multimodal Technol. Interact.*, vol. 4, no. 3, p. 52, Aug. 2020.

[9] B. Alwaely and C. Abhayaratne, "Graph spectral domain feature learning with application to in-air hand-drawn number and shape recognition," *IEEE Access*, vol. 7, pp. 159661–159673, 2019.

[10] R. R. Rachala and M. R. Panicker, "Hand-drawn electrical circuit recognition using object detection and node recognition," *Social Netw. Comput. Sci.*, vol. 3, no. 3, May 2022.

[11] J. Adhikari, M. Aththanayake, C. Kularathna, A. Wijayasiri, and A. Munasinghe, "Deep learning based hand-drawn molecular structure recognition and 3D visualisation using augmented reality," in *Proc. 22nd Int. Conf. Adv. ICT Emerg. Regions (ICTer)*, Nov. 2022, pp. 31–38.

[12] K. Wrobel, R. Doroz, P. Porwik, T. Orczyk, A. B. Cavalcante, and M. Grajzer, "Features of hand-drawn spirals for recognition of Parkinson's disease," in *Proc. Asian Conf. Intell. Inf. Database Syst.*, in Lecture Notes in Computer Science: Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics, vol. 13758, 2022, pp. 458–469.

[13] M. S. Thangakrishnan and K. Ramar, "RETRACTED ARTICLE: Automated hand-drawn sketches retrieval and recognition using regularized particle swarm optimization based deep convolutional neural network," *J. Ambient Intell. Humanized Comput.*, vol. 12, no. 6, pp. 6407–6419, Jun. 2021.

[14] A. Ferdib-Al-Islam and L. Akter, "Early identification of Parkinson's disease from hand-drawn images using histogram of oriented gradients and machine learning techniques," in *Proc. Emerg. Technol. Comput., Commun. Electron. (ETCCE)*, Dec. 2020, pp. 1–6.

[15] S. Roy, A. Bhattacharya, N. Sarkar, S. Malakar, and R. Sarkar, "Offline hand-drawn circuit component recognition using texture and shape-based features," *Multimedia Tools Appl.*, vol. 79, nos. 41–42, pp. 31353–31373, Nov. 2020.

[16] G. Polancic, S. Jagecic, and K. Kous, "An empirical investigation of the effectiveness of optical recognition of hand-drawn business process elements by applying machine learning," *IEEE Access*, vol. 8, pp. 206118–206131, 2020.

[17] Z. Huoming and S. Lixing, "Research on K nearest neighbor identification of hand-drawn circuit diagram," *J. Phys., Conf. Ser.*, vol. 1325, no. 1, Oct. 2019, Art. no. 012233.

[18] M. Gupta, P. Mehndiratta, and A. Bhardwaj, "Object recognition in hand drawn images using machine ensembling techniques and smote sampling," *Commun. Comput. Inf. Sci.*, vol. 1025, pp. 228–239, Jan. 2019.

[19] M. Gupta and P. Mehndiratta, "Analysis and recognition of hand-drawn images with effective data handling," in *Proc. Int. Conf. Big Data Anal.*, in Lecture Notes in Computer Science: Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics, vol. 11932, 2019, pp. 389–407.

[20] M. Moetesum, S. Waqar Younus, M. Ali Warsi, and I. Siddiqi, "Segmentation and recognition of electronic components in hand-drawn circuit diagrams," *ICST Trans. Scalable Inf. Syst.*, vol. 5, no. 16, Apr. 2018, Art. no. 154478.

[21] S. Y. Boulahia, E. Anquetil, R. Kulpa, and F. Multon, "3D multistroke mapping (3DMM): Transfer of hand-drawn pattern representation for skeleton-based gesture recognition," in *Proc. 12th IEEE Int. Conf. Autom. Face Gesture Recognit. (FG)*, May 2017, pp. 462–467.

[22] M. Eicholtz and L. B. Kara, "Characterizing the performance of an image-based recognizer for planar mechanical linkages in textbook graphics and hand-drawn sketches," *Comput. Graph.*, vol. 52, pp. 1–17, Nov. 2015.

[23] J. Chen and N. Takagi, "A pattern recognition method for automating tactile graphics translation from hand-drawn maps," in *Proc. IEEE Int. Conf. Syst., Man, Cybern.*, Oct. 2013, pp. 4173–4178.

[24] S. Ali, N. Aslam, D. Kim, A. Abbas, S. Tufail, and B. Azhar, "Context awareness based sketch-DeepNet architecture for hand-drawn sketches classification and recognition in AIoT," *PeerJ Comput. Sci.*, vol. 9, p. e1186, Apr. 2023.

[25] Z. Li, J. Yang, Y. Wang, M. Cai, X. Liu, and K. Lu, "Early diagnosis of Parkinson's disease using continuous convolution network: Handwriting recognition based on off-line hand drawing without template," *J. Biomed. Informat.*, vol. 130, Jun. 2022, Art. no. 104085.

[26] X. Hou, X. Rong, and X. Yu, "Light-SRNet: A lightweight dual-attention feature fusion network for hand-drawn sketch recognition," *J. Electron. Imag.*, vol. 32, no. 1, Jan. 2023.

[27] J. Fang, Z. Feng, and B. Cai, "DrawnNet: Offline hand-drawn diagram recognition based on keypoint prediction of aggregating geometric characteristics," *Entropy*, vol. 24, no. 3, p. 425, Mar. 2022.

[28] A. Keerthi Priya, N. Gaganashree, K. Hemalatha, J. S. Chembeti, and T. Kavitha, "Ai-based online hand drawn engineering symbol classification and recognition," in *Innovations in Electronics and Communication Engineering* (Lecture Notes in Networks and Systems), vol. 355. Singapore: Springer, 2022, pp. 195–204.

[29] L. Zhang, "Hand-drawn sketch recognition with a double-channel convolutional neural network," *EURASIP J. Adv. Signal Process.*, vol. 2021, no. 1, pp. 1–12, Dec. 2021.

[30] M. Dey, S. M. Mia, N. Sarkar, A. Bhattacharya, S. Roy, S. Malakar, and R. Sarkar, "A two-stage CNN-based hand-drawn electrical and electronic circuit component recognition system," *Neural Comput. Appl.*, vol. 33, no. 20, pp. 13367–13390, Oct. 2021.

[31] H. Weir, K. Thompson, A. Woodward, B. Choi, A. Braun, and T. J. Martínez, "ChemPix: Automated recognition of hand-drawn hydrocarbon structures using deep learning," *Chem. Sci.*, vol. 12, no. 31, pp. 10622–10633, 2021.

[32] Q. Ji, "Research on recognition effect of DSCN network structure in hand-drawn sketch," *Comput. Intell. Neurosci.*, vol. 2021, pp. 1–12, Nov. 2021.

[33] J. Singh, K. Upreti, A. K. Gupta, N. Dave, A. Surana, and D. Mishra, "Deep learning approach for hand drawn emoji identification," in *Proc. IEEE Int. Conf. Current Develop. Eng. Technol.*, 2022, pp. 1–6.

[34] B. Schäfer and H. Stuckenschmidt, "Diagramnet: Hand-drawn diagram recognition using visual arrow-relation detection," in *Proc. Int. Conf. Document Anal. Recognit.*, in Lecture Notes in Computer Science: Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics, vol. 12821, 2021, pp. 614–630.

[35] R. Berari, A. Tauteanu, D. Fichou, P. Brie, M. Dogariu, L. D. Stefan, M. G. Constantin, and B. Ionescu, "Overview of the 2021 imageclef-drawnui task: Detection and recognition of hand drawn and digital website uis," in *Proc. CEUR Workshop*, vol. 2936, 2021, pp. 1121–1132.

[36] B. Schäfer, H. van der Aa, H. Leopold, and H. Stuckenschmidt, "Sketch2BPMN: Automatic recognition of hand-drawn BPMN models," in *Proc. Int. Conf. Adv. Inf. Syst. Eng.*, in Lecture Notes in Computer Science: Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics, vol. 12751, 2021, pp. 344–360.

[37] M. Akter, M. S. Hossain, and K. Andersson, "Hand-drawn emoji recognition using convolutional neural network," in *Proc. IEEE Int. Women Eng. (WIE) Conf. Electr. Comput. Eng. (WIECON-ECE)*, Dec. 2020, pp. 147–152.

[38] C. Pan, J. Huang, J. Gong, and C. Chen, "Teach machine to learn: Hand-drawn multi-symbol sketch recognition in one-shot," *Int. J. Speech Technol.*, vol. 50, no. 7, pp. 2239–2251, Jul. 2020.

[39] D. Fichou, R. Berari, P. Brie, M. Dogariu, L. D. Stefan, M. G. Constantin, and B. Ionescu, "Overview of the 2021 ImageCLEFdrawnUI task: Detection and recognition of hand drawn and digital website UIs," in *Proc. CEUR Workshop*, vol. 2696, 2020.

[40] T. Pan, M. K. Ahsan, and H. Wang, "Hand-drawn electronic component recognition using deep learning algorithm," *Int. J. Comput. Appl. Technol.*, vol. 62, no. 1, p. 13, 2020.

[41] S. Hayat, K. She, M. Mateen, and Y. Yu, "Deep CNN-based features for hand-drawn sketch recognition via transfer learning approach," *Int. J. Adv. Comput. Sci. Appl.*, vol. 10, no. 9, pp. 438–448, 2019.

[42] S. Dey, A. Dutta, J. Lladós, A. Fornés, and U. Pal, "Shallow neural network model for hand-drawn symbol recognition in multi-writer scenario," in *Proc. 14th IAPR Int. Conf. Document Anal. Recognit. (ICDAR)*, vol. 2, Nov. 2017, pp. 31–32.

[43] M. Rabbani, R. Khoshkangini, H. S. Nagendraswamy, and M. Conti, "Hand drawn optical circuit recognition," *Proc. Comput. Sci.*, vol. 84, pp. 41–48, Jan. 2016.

[44] Y. Xu and C. Y. Suen, "Recognition of graphological wartegg hand-drawings," in *Proc. Int. Graphonomics Conf.*, in Lecture Notes in Computer Science: Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics, vol. 13424, 2022, pp. 174–186.

[45] B. U. Mahmud, R. D. Shuva, S. S. Bose, M. M. R. Majumder, B. Jahan, and M. M. Alam, "A proposed method for recognizing complex hand drawn graphs using digital geometric techniques," in *Proc. Int. Conf. Sustain. Technol. Ind. 4.0 (STI)*, Dec. 2019, pp. 1–6.

[46] W. Szwoch and M. Mucha, "Recognition of hand drawn flowcharts," *Adv. Intell. Syst. Comput.*, vol. 184, pp. 65–72, Jan. 2013.

[47] K. Aruleba, S. Ewert, I. Sanders, and M. Raborife, "Pre-processing and feature extraction technique for hand-drawn finite automata recognition," in *Proc. IST-Africa Week Conf. (IST-Africa)*, May 2018, pp. 1–9.

[48] V. Deufemia, M. Risi, and G. Tortora, *Hand-Drawn Diagram Recognition With Hierarchical Parsing: An Experimental Evaluation*. Heidelberg, Germany: Physica, 2013, Art. no. 9783790827897.

[49] H. Cecotti, C. Boumedine, and M. Callaghan, "Hand-drawn symbol recognition in immersive virtual reality using deep extreme learning machines," *Commun. Comput. Inf. Sci.*, vol. 709, pp. 80–92, 2017.

[50] M. Bresler, D. Průša, and V. Hlaváč, "Online recognition of sketched arrow-connected diagrams," *Int. J. Document Anal. Recognit.*, vol. 19, no. 3, pp. 253–267, Sep. 2016.

[51] M. Bresler, T. Van Phan, D. Prusa, M. Nakagawa, and V. Hlavác, "Recognition system for on-line sketched diagrams," in *Proc. 14th Int. Conf. Frontiers Handwriting Recognit.*, Sep. 2014, pp. 563–568.

[52] A. M. Awal, G. Feng, H. Mouchère, and C. Viard-Gaudin, "First experiments on a new online handwritten flowchart database," *Proc. SPIE*, vol. 7874, pp. 1–10, Jan. 2011.

[53] M. Eitz, J. Hays, and M. Alexa, "How do humans sketch objects?" *ACM Trans. Graph.*, vol. 31, no. 4, pp. 1–10, Jul. 2012.

[54] C. Tirkaz, B. Yanikoglu, and T. Metin Sezgin, "Sketched symbol recognition with auto-completion," *Pattern Recognit.*, vol. 45, no. 11, pp. 3926–3937, Nov. 2012.

[55] P. Sangkloy, N. Burnell, C. Ham, and J. Hays, "The sketchy database: Learning to retrieve badly drawn bunnies," *ACM Trans. Graph.*, vol. 35, no. 4, pp. 1–12, Jul. 2016.

[56] A. Godil, Bo, Y. Lu, and Tobias, "Shrec#146;13 track: Large scale sketch-based 3D shape retrieval," in *Proc. Eurograph. Workshop 3D Object Retr.*, Girona, Spain, May 2013, pp. 1–6.

[57] R. Niels, D. Willems, and L. Vuurpijl, "The nicicon database of handwritten icons for crisis management," in *Proc. 1st Int. Conf. Frontiers Handwriting Recognit.*, 2009, pp. 296–301.

[58] H. O. Brinkhaus, A. Zielesny, C. Steinbeck, and K. Rajan, "Decimer-hand-drawn molecule images dataset," *J. Cheminform.*, vol. 14, pp. 1–13, Jan. 2022.

[59] C. R. Pereira, D. R. Pereira, F. A. Silva, J. P. Masieiro, S. A. T. Weber, C. Hook, and J. P. Papa, "A new computer vision-based approach to aid the diagnosis of Parkinson's disease," *Comput. Methods Programs Biomed.*, vol. 136, pp. 79–88, Nov. 2016.

[60] M. H. Zaki, S. Islam, and J. Wasim, "Hand drawn graph recognition," in *Proc. 10th Int. Conf. Comput. Sustain. Global Develop.*, Mar. 2023, pp. 1515–1520.

[61] S.-J. Hsiao, K.-Y. Lian, and W.-T. Sung, "Real-time recognition of hand-drawn patterns using an innovative web-based approach," in *Proc. Int. Symp. Comput., Consum. Control*, Jul. 2016, pp. 22–25.

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