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SURVEY

A Systematic Review of Deep Learning Microalgae Classification and Detection

DINA M. MADKOUR[1,2], MOHD IBRAHIM SHAPIAI[1,3], (Member, IEEE), SHAZA EVA MOHAMAD[1], HESHAM HAMDY ALY[4], ZOOL HILMI ISMAIL[1,3], (Senior Member, IEEE), AND MOHD ZAMRI IBRAHIM[5]

[1]Malaysia-Japan International Institute of Technology (MJIIT), Universiti Teknologi Malaysia, Jalan Sultan Yahya Petra, Kuala Lumpur 54100, Malaysia
[2]Computer Engineering Department, Arab Academy for Science, Technology and Maritime Transport, Cairo 11835, Egypt
[3]Centre for Artificial Intelligence and Robotics iKohza, Malaysia-Japan International Institute of Technology, Universiti Teknologi Malaysia, Kuala Lumpur 54100, Malaysia
[4]Electronics and Communications Engineering Department, Arab Academy for Science, Technology and Maritime Transport, Giza 12577, Egypt
[5]Faculty of Electrical and Electronics Engineering Technology, Universiti Malaysia Pahang, Pekan, Pahang 26600, Malaysia

Corresponding author: Dina M. Madkour (dinamadkour@aast.edu)

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ABSTRACT Algae represent the majority of the diversity on Earth and are a large group of organisms that have photosynthetic properties that are important to life. The species of algae are estimated to be more than 1 million, they play an important role in many fields such as agriculture, industry, food, and medicine. It is important to determine the type of algae, to determine if it is harmful or useful, and to indicate the health of the ecosystem, water quality, health, and safety risks. The conventional process of classifying algae is difficult, tedious, and time-consuming. Recently various computer vision techniques have been used to classify algae to overcome challenges and automate the process of classification. This paper presents a review of research done on image classification for microorganism algae using machine learning and deep learning techniques. The paper focuses on three important research questions to highlight the challenges of classifying microalgae. A systematic literature review or SLR has been conducted to determine how deep learning and machine learning have improved and enhanced automatic microalgae classification rather than manual classification. 51 articles have been included from well-known databases. The outcome of this SLR is beneficial due to the detailed analysis and comprehensive overview of the algorithms and the architectures and information about the dataset used in each included article. The future work focuses on getting a large dataset with high resolution, trying different methods to manage imbalance problems, and giving more attention to the fusion of deep learning techniques and traditional machine learning techniques.

INDEX TERMS Algae detection, algae classification, deep learning, deep network, deep architecture, microalgae, systematic literature review.

I. INTRODUCTION

A major class of eukaryotic photosynthetic organisms is algae. Chlorophyll is one of the photosynthetic pigments found in algae. They are a member of a polyphyletic group, which refers to a collection of species that are not all closely related and do not have a common ancestor. Algae have a feature common with vascular plants where they are eukaryotes capable of photosynthesis with chlorophyll as their primary pigment but other morphoanatomical features among vascular plants such as true roots, stems, and leaves [1].

Most algae are aquatic while others are terrestrial that can be found on moist soil, trees, and rocks. Some of them are unicellular and others are multicellular, they can live in colonies or have a leafy appearance such as seaweeds, also the size of species varies from microscopic to giant kelp with millions

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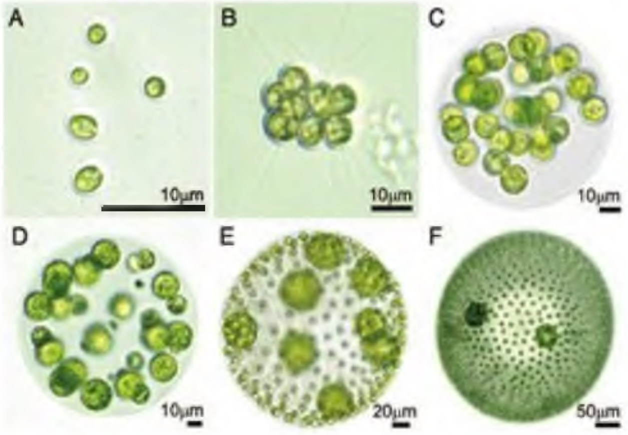

FIGURE 1. Examples of unicellular and multicellular algae.

of cells. The two major types of algae based on cellularity are microalgae and macro-algae, where microalgae are small and unicellular algae species that live either singly or in colonies and they need a microscope to be seen, while the macro-algae are large and multicellular species of algae that can be seen without the aid of a microscope and are visible to the naked eye, they are commonly named seaweeds [2]. Both types of algae are important contributors to atmospheric oxygen, and they are considered a food source for many aquatic habitats and potential sources of biofuel production. Figure 1 [3] shows some examples and the difference between unicellular and multicellular algae.

Algae can be found in either freshwater or saltwater. Also, algae don't cause harm to humans they are harmless and most of the species are useful to humans, but certain species of algae can form algal blooms [4], this is the case where the population of algae in water bodies such as rivers or lakes increases rapidly. This can cause discoloration and a strange odor of the water, where this can have negative effects on the health of humans and the environment.

Algae are important due to their ecological role as oxygen producers, as algae account for half of the photosynthetic production of organic material on Earth. Most aquatic life and animals use algae as their food base [1]. Algae are being used in different industries, as a source of food, and some pharmaceutical products for humans. They can also be used as fertilizers. Seaweed, which is a common name for different species of algae, is an important source of nutrients such as vitamins, iodine, potassium, iron, magnesium, and calcium [5]. Some species are important sources of many compounds including fiber, proteins, polysaccharides, and lipids. Of all the known species identified, only 50 are in widespread commercial use.

Algae can be used in many industries [6] including drinks, toothpaste, nutritional supplements, crude oil production, biofuels [7], drugs, and cosmetics. Algae can also be used to produce agar which is used in microbiological studies as a growth medium [8]. Agar is a gelatin-like product obtained from the cell walls of some species of red algae. Algae at the beginning of the 1830s were classified into major groups of red, green, and brown algae based on their color. The colors are a reflection of different chloroplast pigments including chlorophylls, phycobiliproteins, and carotenoids [9]. Besides these three main pigment groups, many others are recognized by phycologists. For the classification of algae, some suffixes were recommended by The International Code of Botanical Nomenclature (ICBN) [10]. These suffixes are '-phyta' for division, '-phyceae' for class, '-phycidae' for sub-class, '-ales' for order, '-inales' for sub-order, '-aceae' for family, and '-oideae' for sub-family.

Algae can be categorized into seven major types, each with distinct sizes, functions, and colors. Those seven categories of algae are the most well-known and each has its characteristics, and each type has a few to thousands of species. The different divisions include:

- Euglenophyta (Euglenoids)
- Chrysophyta (Golden-brown algae and Diatoms)
- Pyrrophyta (Fire algae, dinoflagellates)
- Chlorophyta (Green algae)
- Rhodophyta (Red algae)
- Phaeophyta (Brown algae)
- Xanthophyta (Yellow-green algae)

Algae can be categorized into microalgae and macroalgae. This paper focuses on microalgae only. It is important to identify and differentiate between microalgae species due to their wide applications in different areas. Microalgae have a significant role in the environmental balance and are important for life on Earth. Microalgae are very diverse. Their species are estimated to be about 200,000 to 800,000. They can do photosynthesis similar to higher plants which is important for life on earth and the production of oxygen. Also, microalgae can grow 10 to 50 times faster than higher plants. Cultivation of microalgae either in open ponds or closed photobioreactors is less seasonality, simple, and not expensive and can take place in low-productive or non-arable land. The harvesting of microalgae is short and can be used directly or after some processing [11].

Another ecological and environmental importance of microalgae is that they reduce the effects of water and soil pollution with industrial waste, so they are considered the main requirement for the conservation of biodiversity. Also, microalgae improve the physical and chemical characteristics of the soil. Moreover, microalgae have a role in the stimulation of plant growth and help in maintaining the ecological balance [11]. Since microalgae are very sensitive to light, temperature, and pollution so they are considered an excellent indicator of ecosystem changes. Microalgae have in their cell structure many lipids, so they are becoming an interest as a biofuel feedstock and are also involved in the production of biodiesel [12].

To make microalgae detection and classification, it can be done by human conventional techniques or by using computer vision methods. The human conventional techniques take place by the manual classification of algae in the microscopic images which is a tedious, labor-intensive, and time-consuming process [13]. A highly skilled specialist is required to do this process manually, to distinguish between different species as the morphological differences between them are very subtle. This has led to a considerable amount of effort in research to be directed to developing systems to automatically analyze, detect and classify algae images.

Computer vision techniques are widely used to analyze digital images, they are being used in many applications and fields such as medical images, underwater images, spatial images, and other biological images. For detecting, counting, identifying, and classifying algae in images this can take place by using computer vision techniques. Some developed methods and tools are used for online monitoring, some are used to measure the density of microalgae in water, and some were developed to help in the process of recognition by using enhancing images, eliminating noise, and segmentation using edge extraction methods [14]. Nowadays, Artificial intelligence (AI) plays a main role in computer vision for several applications like artificial neural networks (ANN) and deep neural networks that can detect and recognize algae in images automatically.

For the process of microalgae image classification to be done it passes through five main steps [13], sample collection, image acquisition, image processing, feature extraction and selection, and classification using ANN.

ANNs consist of artificial neurons that can solve classification problems. Artificial neural networks work based on two steps. The first step is using the feature vector extracted for microalgae to train the network. The second step is to test and validate the network.

Deep learning algorithms and techniques can be used for several tasks for microalgae such as classification, identification, segmentation, and other tasks. Deep learning networks can be either used for supervised learning, unsupervised learning, and hybrid learning [19] For each of the mentioned techniques, the dataset used for training or testing the network differs in characteristics from one technique to another based on the learning method such as labeled data., unlabeled labeled data, and the dataset size, that will be discussed in the following section.

Microalgae systems for classification are mostly based on traditional computer vision techniques, where the features are extracted and then the system is trained on this set of input features. Recently, automated microalgae classification systems based on convolutional neural networks (ConvNets) have been employed. Image classification techniques are diverse from either traditional techniques or modern learning techniques [15]. The traditional techniques include decision trees, random forests, KNN, support vector machine (SVM), and neural networks, while modern techniques include CNN and deep neural networks.

II. DEEP LEARNING

Deep learning is a special form of machine learning [16]. The workflow of machine learning starts with extracting relevant features manually from the images. Then use the features to create a model that categorizes the objects in the image. On the other hand, the workflow of deep learning the process of extracting the relevant features is done automatically. The network is given the data in raw format and the task to perform, such as classification, and the network learns how to do this task automatically, this process is called "end-to-end learning."

A key advantage of using deep learning networks is that the performance of the network often continues to improve as the size of the data increases. A very large amount of data is required to have a successful deep learning application. Thousands of images and a graphical processing unit (GPU) are required to rapidly process the data and train the model. [17].

Deep learning models have a long training time because of the huge number of parameters of the model, but on the other side, it takes a short time during the testing phase as compared to other machine learning algorithms. In recent years, deep learning has been applied successfully to numerous problems in different application areas, such as natural language processing, sentiment analysis, cybersecurity, business, virtual assistants, visual recognition, healthcare, robotics, and many more [18]. Various deep learning techniques that include discriminative learning, generative learning, as well as hybrid learning models are employed in these application areas.

Deep learning models include convolution neural networks, recurrent neural networks, auto-encoders, deep belief networks, and many more. Deep learning consists of three sequential stages [18]:

1- Understand data and make data pre-processing.
2- Building and training the deep learning model.
3- Validation and interpretation.

Choosing between either deep learning techniques or conventional machine learning techniques is based on both the conditions and the differences between both techniques.

A. DIFFERENCE BETWEEN DEEP LEARNING AND CONVENTIONAL MACHINE LEARNING TECHNIQUES

The performance of the networks as the data grows exponentially is the most significant distinction between deep learning and regular machine learning [16].

1) DATA DEPENDENCIES

To build a data-driven model for a specific problem, deep learning depends on a large amount of data. Because deep learning algorithms often have poor performance when the data is small. In this case, the standard machine learning algorithms performance will be improved.

2) HARDWARE DEPENDENCIES

For the process of training a model with large datasets, deep learning algorithms require large computational operations. As the number of computations increases, the more the advantage of a GPU over a CPU, and the GPU is mostly used to optimize the operations efficiently. So, GPU hardware is necessary to work properly with the

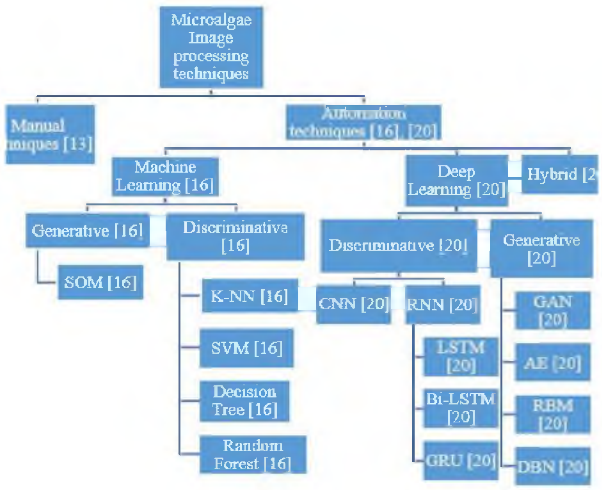

FIGURE 2. Methods to perform algae classification, detection, and segmentation [15], [19].

deep learning models. Therefore, deep learning relies more on high-performance machines with GPUs than standard machine learning methods.

3) FEATURE ENGINEERING PROCESS

Feature engineering is the process of extracting features (characteristics, properties, and attributes) from raw data. Extracting high-level characteristics directly from the data is a fundamental distinction between deep learning and machine learning techniques.

Thus, Deep learning decreases the time and effort required to construct a feature extractor for each problem.

4) MODEL TRAINING AND EXECUTION TIME

For the deep learning algorithms to train, it takes a long time due to many parameters that exist. The deep learning model can complete training in more than one week. When compared to machine learning algorithms, machine learning takes little time, only seconds to a few hours.

In the testing phase, deep learning algorithms take extremely little time to run, when compared to certain machine learning methods. Table 1 summarizes the difference between deep learning techniques and conventional machine learning techniques from several aspects such as performance of classification, nature, type and amount of data and features, etc. [16], [58].

B. DEEP LEARNING TECHNIQUES CATEGORIES

The algae image processing tasks such as classification, detection, and segmentation process can be done using different methods and techniques that are shown Figure 2 [15], [19]. Those techniques will be discussed briefly later. Deep learning techniques can be categorized into three categories, supervised learning techniques, unsupervised learning techniques, and hybrid learning techniques.

Algae can be classified or detected using conventional manual techniques in laboratories using microscopic images. In Automation techniques, conventional machine learning techniques such as K-NN, SVM, decision trees, and random forests are being used for the classification of algae in images. While in deep learning the discriminate can be used to perform other tasks rather than classification, where they can be used for the detection of algae in images or to make segmentation for the algae such as CNN and its invariants, and RNN.

Deep learning can be used for microalgae classification or detection, or other tasks as follows:

1- Deep networks for **supervised or discriminative learning** that are used to provide a discriminative function in supervised deep learning or classification applications. It is a task-driven approach that uses a training dataset that is labeled [19]. They mainly include Multi-Layer Perceptron (MLP), Convolutional Neural Networks (CNN or ConvNet), and Recurrent Neural Networks (RNN), along with their variants.

2- Deep networks for **unsupervised or generative learning** that are used to characterize the high-order correlation properties or features for pattern analysis or synthesis, thus can be used as preprocessing for the supervised algorithm [19]. It is a data-driven process that works on unlabeled datasets.

3- Deep networks for **hybrid learning** integrates both supervised and unsupervised models [19].

III. SYSTEMATIC LITERATURE REVIEW

The three-step process of plan, conduct, and report has been observed in conducting this SLR. In the planning phase, defining the research question is done, then establishing a review protocol, specifying the sources of publications, search terms, and the criteria for selecting research to be included. In the second step, by following the review protocol the literature was collected. To answer the questions the selected literature was analyzed, extracting, and synthesizing the required data. Finally, documenting the review results, addressing the research questions and the objectives of the SLR.

A. RESEARCH QUESTIONS

The main target of this review is to determine how deep learning is being applied and used for microalgae classification and detection and to determine how the recognition frameworks and applications are being implemented using deep networks. As a result, the following Research Questions (RQs) have been framed:

1- What kind of data has been used to train and test the network, and the data accessibility?

2- What learning algorithms are applied and what deep network architectures are applied?

3- What are the challenges, issues, and future directions of this work?

TABLE 1. Deep learning vs. conventional machine learning [16], [58].

Field of Comparison	Deep Learning versus Machine Learning
Image classification	• Deep learning achieves better classification accuracy than classical machine learning.
Scaling with data.	• Compared to traditional ML techniques, deep networks scale better with more data. • Using more data improves the accuracy of a deep network. • In classical machine learning algorithms, to improve accuracy more complex methods are often required.
Feature engineering	• In deep networks, there is no need for extracting features, the data is passed directly to the network. • In machine learning algorithms, it is required to extract complex features, and perform data analysis on the dataset, then for easier processing, a reduction of dimension is done. Then to pass the features to the machine learning algorithm the best features must be carefully selected.
Adaptable and transferable	• Deep learning techniques are more easily adaptable to different domains and applications than classical machine learning algorithms. • In classical machine learning the knowledge base of classical machine learning for different domains and applications is different within each area.
Size of dataset	• Extremely large datasets are required for deep networks, but an available large dataset is not always ready for many applications, and acquiring a suitable dataset will be an expensive and time-consuming process. • Machine learning algorithms often outperform deep networks when the dataset is small.
Cost	• High-end GPUs are required for deep networks to train big data within a reasonable time. These GPUs are costly yet without them training deep networks to high performance would not be practically feasible. • A decent CPU can be used to train a machine learning model, without requiring the best hardware. Because they aren't so computationally expensive, in a shorter period they can iterate faster and try out many different techniques.

To answer the three research questions each article has been reviewed and followed a focused approach. All the gathered data is reported in a comprehensive way to have a complete picture.

B. REVIEW PROTOCOL

The procedures adopted for this SLR such as search sources, search terms, inclusion criteria, and exclusion criteria are specified as followed:

1) SEARCH SOURCES

The data were selected and extracted from three popular scientific databases which are Scopus, IEEE Xplore, Springer Link, and manual search.

2) SEARCH TERMS

The investigated topic combines two main search terms which are: "Deep Learning," and "Algae Classification." Each term has an alternative word that can be searched with, the terms were combined by the "OR" operator. To concatenate individual search strings the "AND" operator is used to form a search query. To find the maximum number of literature full search text has been employed. Figure 3 shows the complete search queries.

3) INCLUSION CRITERIA

This study focuses on the applications of classification and detection of microalgae using deep learning. The studies included are published in the English language and use deep learning algorithms for classification, detection, segmentation, identification, or any other task related to microalgae classification and detection. All studies included in this research use microscopic algae images. For a wider search spectrum, no limits were set in the subject area. However, since deep learning is an emerging field, the literature done in response to the search queries in recent years, the period of the selected articles extends over six years 2017-2022. The included literature chosen on the explored topic includes journal articles, conference proceedings, and book sections.

4) EXCLUSION CRITERIA

This review paper includes studies on the classification or detection of algae from microscopic images using deep learning algorithms. Some publications were not included that use other forms of images such as synthetic aperture radar (SAR) images, ground images, and satellite images, and publications that require hardware development or are based on IoT. Also, studies that use chemical reactions on water samples to determine and classify algae based on type or reaction are excluded.

C. LITERATURE COLLECTION

The literature search was performed by specifying search strings for each database as shown in Figure 3, with a total of 518 publications. According to the inclusion and exclusion criteria predefined, the search results were assessed from each database. In the initial screening, every publication was evaluated based on the title, abstract and quick review of the text to

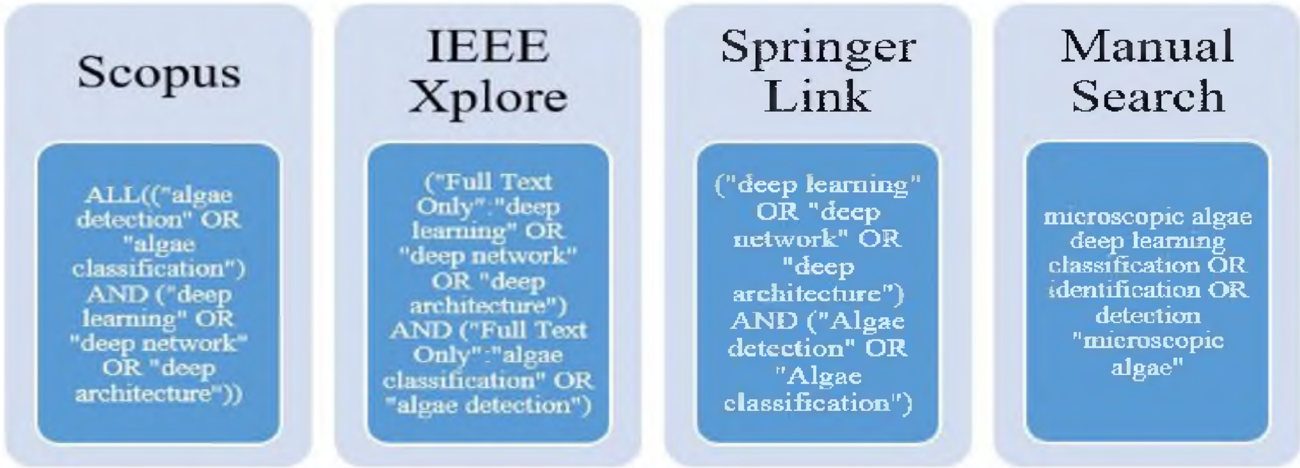

FIGURE 3. Search query for each database.

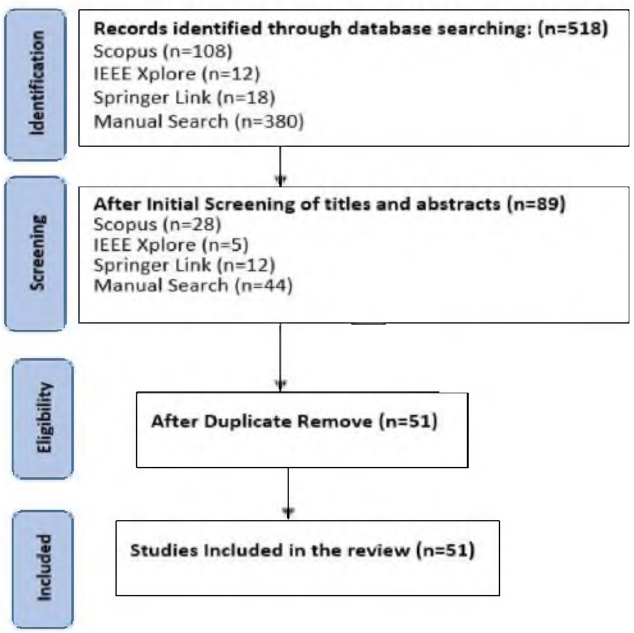

FIGURE 4. Preferred reporting items for systematic review and meta-analysis (PRISMA) diagram.

decide if it will be included or excluded from the review. After this filtration, the number of publications was reduced to 89 publications. After removing the duplicated publications 51 publications were included to be used in this systematic literature review (SLR). Figure 4 shows the data selection process by Preferred Reporting Items for Systematic Review and Meta-analysis (PRISMA) framework.

IV. RESULTS

The publication selected are listed in Table 2 with the title of publication, source of publication, year of publication, and source of publication. Figure 5 shows the publication distribution from 2017 to 2022. In the yearly distribution, it is noticeable that there is some increase in the literature. Moreover, out of the 51 articles selected, 29 were published in journals, 21 in conferences, and 1 book chapter.

V. DISCUSSION

Five of the included publications are review papers which are [66], [67], [68], [69], and [70]. In [66], Priya Rani et al. presented a review of machine learning and deep learning approaches for the recognition of microorganisms such as bacteria, algae, protozoa, and fungi from the year 1995 to 2021. It reviewed 100 papers but only 28 are discussing algae. Different image analysis methods for image pre-processing, feature extraction and selection, classification techniques, challenges, and performance metrics were analyzed and discussed by the authors. In [67], Chin Li et al. presented a comprehensive overview of microorganism classification using Content-based microscopic image analysis (CBMIA) methods, applied in the field of microorganisms' classification. For image pre-processing, feature extraction, post-processing, classification, and evaluation different image analysis methods were analyzed and discussed by the authors. The review contains about 240 papers in a time series from 1978 to 2017. Also, in [68] Chen Li et al. presented a review of CBMIA using ANN approaches for around 60 papers from the 1990s to 2019, including classical ANNs, deep ANNs, and methodology analysis in the CBMIA field. CBMIA systems are used for microorganisms analysis because they need only visual information. Zhang et al. in [69] conducted a review to discuss the characteristics of the Microorganisms' image analysis based on artificial neural networks using classical and deep neural networks. This review summarizes 95 papers in a time series from 1992 to 2020. The summarized papers are related to classification, segmentation, detection, counting, feature extraction, image enhancement, and data augmentation tasks.

In [70], Ma et al. presented a survey for object detection technologies in microorganism image analysis, the

TABLE 2. Title, source, year, and type.

No.	Ref.	Publication Title	Source	Year/Type
1	[20]	Multi-Target Deep Learning for Algal Detection and Classification	IEEE	2020 conference
2	[21]	Dodge or disinfect? Classifying Algae in Small-Scale Water Bodies via Low-Cost Deep Neural Networks	IEEE	2021 conference
3	[22]	Comparison of CNN and MLP classifiers for algae detection in underwater pipelines	IEEE & Scopus	2017 conference
4	[23]	Neural-Network Based Algorithm for Algae Detection in Automatic Inspection of Underwater Pipelines	Springer	2017 conference
5	[24]	Chlorella Algae Image Analysis Using Artificial Neural Network and Deep Learning	Springer	2017 Chapter
6	[25]	A coarse to fine framework for recognizing and locating multiple diatoms with highly complex backgrounds in forensic investigation	Springer & Scopus	2022 Journal
7	[26]	Classification of Microscopic Algae: An Observational Study with AlexNet	Springer	2020 conference
8	[27]	A New Shape Descriptor and Segmentation Algorithm for Automated Classifying of Multiple-morphological Filamentous Algae	Springer	2019 conference
9	[28]	Automatic plankton image classification combining multiple view features via multiple kernel learning	Springer	2017 Journal
10	[29]	Deep learning applied to SEM images for supporting marine coralline algae classification	Scopus	2021 Journal
11	[30]	Weighted Mask R-CNN for Improving Adjacent Boundary Segmentation	Scopus	2021 Journal
12	[31]	Automatic Identification of Diatom Morphology using Deep Learning	Scopus	2020 conference
13	[32]	Automated red tide algae recognition by the color microscopic image	Scopus	2020 conference
14	[33]	A low-cost automated digital microscopy platform for automatic identification of diatoms	Scopus	2020 Journal
15	[34]	Deep learning based ResNeXt model in phycological studies for future	Scopus	2020 Journal
16	[35]	Fully convolutional neural network for detection and counting of diatoms on coatings after short-term field exposure	Scopus	2020 Journal
17	[36]	Identification and enumeration of cyanobacteria species using a deep neural network	Scopus	2020 Journal
18	[37]	ResNeXt convolution neural network topology-based deep learning model for identification and classification of Pediastrum	Scopus	2020 Journal
19	[38]	Semantic versus instance segmentation in microscopic algae detection	Scopus	2020 Journal
20	[39]	A Deep Learning based CNN framework approach for Plankton Classification	Scopus	2019 conference
21	[40]	Computer vision-based algae removal planner for multi-robot teams	Scopus & IEEE	2019Conference
22	[41]	Enhancing red tide image recognition using hierarchical learning approach based on semantic feature	Scopus	2019 conference
23	[42]	Algal morphological identification in watersheds for drinking water supply using neural architecture search for convolutional neural network	Scopus	2019 Journal
24	[43]	Texture and shape information fusion of convolutional neural network for plankton image classification	Scopus	2018 conference
25	[44]	Deep learning for microalgae classification	Scopus	2017 conference
26	[45]	Microalgae classification based on machine learning techniques	Scopus	2021 Journal
27	[46]	Phenotypic Analysis of Microalgae Populations Using Label-Free Imaging Flow Cytometry and Deep Learning	ACS Publications	2021 Journal
28	[47]	Morphology-based identification and classification of Pediastrum through AlexNet Convolution Neural Network	IOP Conference Series	2021Conference
29	[48]	Application of a convolutional neural network to improve automated early warning of harmful algal blooms	Springer	2021 Journal
30	[49]	Microalgae Detection Using a Deep Learning Object Detection Algorithm, YOLOv3	Korean Society	2021 Journal
31	[50]	Automatic Identification of Harmful Algae Based On Multiple Convolutional Neural Networks and Transfer Learning	Springer	2021 Journal
32	[51]	Deep Active Learning for In Situ Plankton Classification	Springer	2018 conference
33	[52]	Lights and pitfalls of convolutional neural networks for diatom identification	SPIE	2018Conference
34	[53]	Transferred parallel convolutional neural network for large imbalanced plankton database classification	IEEE	2018 conference
35	[54]	Automated plankton image analysis using convolutional neural networks	ASLO	2018 Journal
36	[55]	Intelligent plankton image classification with deep learning	Inderscience	2018 Journal
37	[56]	Deep learning and transfer learning features for plankton classification	Science Direct	2019 Journal
38	[57]	Diatom Classification Including Morphological Adaptations Using CNNs	Springer	2019 conference
39	[58]	Deep Learning Versus Classic Methods for Multi-taxon Diatom Segmentation	Springer	2019 conference
40	[59]	Deep Learning-Based Algal Detection Model Development Considering Field Application	Scopus	2022 Journal
41	[60]	Diffeomorphic transforms for data augmentation of highly variable shape and texture objects	Scopus	2022 Journal
42	[61]	Computer Vision Based Deep Learning Approach for the Detection and Classification of Algae Species Using Microscopic Images	Water	2022 Journal
43	[62]	Improving deep learning-based segmentation of diatoms in gigapixel-sized virtual slides by object-based tile positioning and object integrity constraint	bioRxiv	2022 Journal
44	[63]	Multiclass-Classification of Algae using Dc-GAN and Transfer Learning	IEEE	2022 conference
45	[64]	Segmentation of diatoms using edge detection and deep learning	Scopus	2022 Journal
46	[65]	An improved algae-YOLO model based on deep learning for object detection of ocean microalgae considering aquacultural lightweight deployment	Scopus	2020 conference
47	[66]	Machine Learning and Deep Learning Based Computational Approaches in Automatic Microorganisms Image Recognition: Methodologies, Challenges, and Developments	Springer &Scopus	2021 Journal
48	[67]	A survey for the applications of content-based microscopic image analysis in microorganism classification domains	Springer & Scopus	2019 Journal

TABLE 2. *(Continued.)* **Title, source, year, and type.**

49	[68]	A brief review for content-based microorganism image analysis using classical and deep neural networks	Scopus & Springer	2018 conference
50	[69]	Applications of artificial neural networks in microorganism image analysis: a comprehensive review from conventional multilayer perceptron to popular convolutional neural network and potential visual transformer	Springer	2022 Journal
51	[70]	A state-of-the-art survey of object detection techniques in microorganism image analysis: from classical methods to deep learning approaches.	Scopus & Springer	2022 Journal

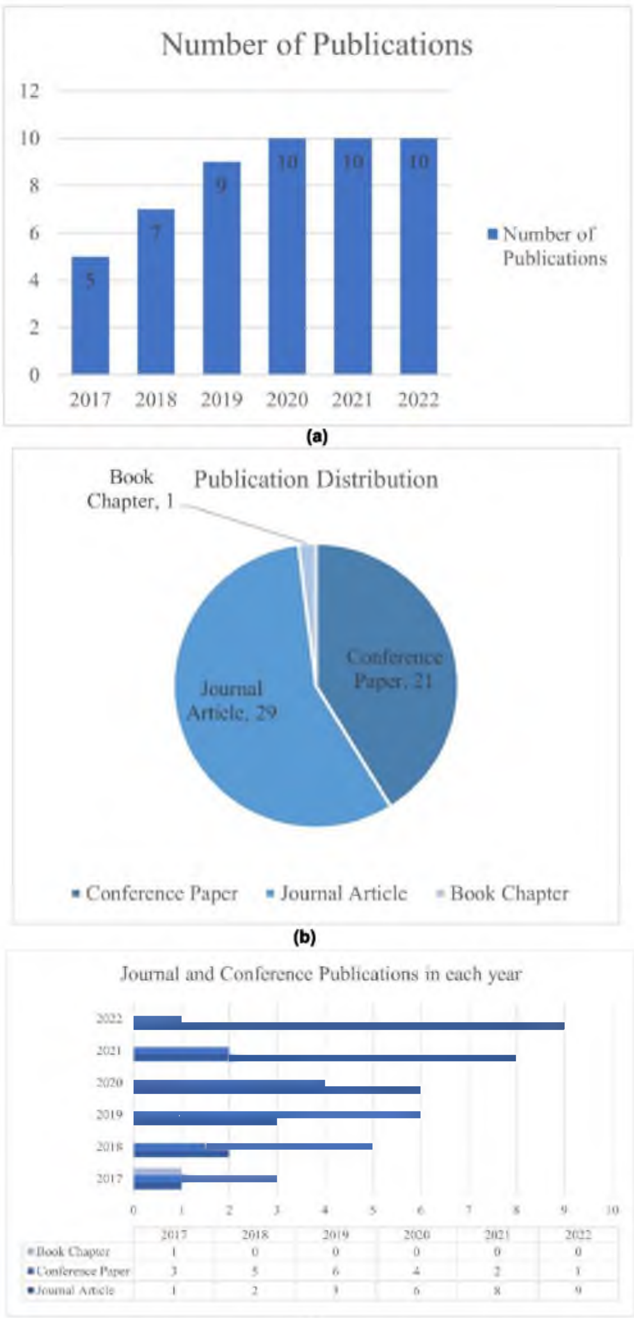

FIGURE 5. **Publication distribution: (a) Yearly publications (b) Type of publication (c) type of publication based on yearly distribution.**

methods are analyzed in chronological order and summarized 142 papers from 1985 to 2022, it reviewed, analyzed, and summarized methods from traditional image processing and traditional machine learning to deep learning methods, also introduced some potential methods such as visual transformers.

The five review papers mentioned several micro-organisms rather than algae which is the main micro-organism for this SLR. Also, the five review papers lack some information and data about each publication included compared to the information that will be included in this SLR based on the three RQs mentioned before.

In [66] The method is mentioned very briefly without any details, no details about the dataset, only the number of classes for the dataset is mentioned, but the size of the data set, name of the dataset, accessibility of the dataset, and any preprocessing or augmentation for the dataset is not mentioned, and no information about the performance or accuracy is mentioned, also no information about training and testing the network is mentioned.

Moreover, the issues and the future work of each publication are not mentioned. While in [67] the included publications were divided from the application domain and time series domain, it contains more details than those mentioned in [66], where the accuracy is mentioned for each publication if available, also more details about the dataset are mentioned such as the number of classes, and the number of samples. But this paper still lacks more information about the method used, type of training, nature of data, dataset name or accessibility, and the issues and future work.

In [68], publications about different micro-organisms such as bacteria, algae, protozoa, and fungi are included. All the publications reviewed in this review paper perform the task of recognition, also the method is mentioned briefly, and the number of samples and the number of classes of the dataset are mentioned without more details about the dataset such as the type of access. The only performance metric mentioned is accuracy. No details about the type of training of the network, the architecture of the network, the name of the dataset, preprocessing of the dataset, and finally nothing is mentioned about the challenges and issues of each included publication.

In [69] there is no information or details about the datasets used in each included publication in the review, also the papers are reviewed from the perspective of classical or deep neural networks and from the perspective of different tasks such as classification, segmentation, counting, and feature extraction. This review also focuses on the development history of ANNs in the microorganism image analysis field.

In [70] there is a lack of enough information about the methods used in each publication, the training and testing procedure, also there are no details about the dataset mentioned. It mentioned the micro-organism type that needs to be detected, the method applied, and the evaluation.

The things that make this SLR relevant are the three RQs mentioned where each RQ covers as many details as possible as will be mentioned in the next sections and sub-sections. Also, this SLR covers more information about the datasets used than the information included in the previously mentioned review papers, such as type of access, name of the dataset, the origin of the dataset, and any preprocessing or augmentation applied to the dataset.

In this SLR the division of the dataset for training and testing of the network is mentioned and the type of training is mentioned. Finally, the 3rd RQ of this SLR is not covered with details by any of the previously mentioned review papers, where the challenges, issues, and future work of each publication will be mentioned, which is considered a very important point to cover, where this helps to be familiar with the common issues in algae image processing tasks to avoid those issues and problems and to find solutions to those challenges that will help to extend the field of research for algae and machine learning and also helps in improving the performance of neural networks.

After reviewing the five-review publications the remaining 46 publications included in this SLR are reviewed to answer the three RQs mentioned above, for each publication, a detailed study has been conducted, and the needed data is extracted. Each publication was analyzed from the perspective of the problem to solve, the main method, the learning algorithm used, the data used, the accessibility of data, data size, issues, and future work. In the following sub-section, the discussion on three specific RQs is presented.

A. WHAT WAS THE NATURE OF THE DATA USED FOR THE NETWORK AND THE DATA ACCESSIBILITY? – RQ1

A review of the sources and types of microalgae data for deep network training and evaluation is discussed in this sub-section. For the task of algae classification or detection a good, diverse, and balanced dataset is required for deep learning methods. In this domain, not all algae datasets are made publicly available. However, few are open access for the public either by request, or are available online, or are available from the specific lab while the rest are not publicly available. The summary information of the datasets is tabulated in Table 3.

After reviewing the publications from the dataset perspective, there are a total of 13 publications that use open access datasets, 28 publications that use limited access datasets, 2 publications that use both limited access and open access datasets, and 3 publications that use open access datasets that are available under request. From these statistics, most of the algae datasets have limited access and only a few datasets are available publicly which limits the diversity of algae images and types that can be used in machine learning processes for algae classification or detection. The limited access datasets are self-collected by the research team of each publication and collected for specific purposes and specific types of algae.

It is important to make the datasets publicly available to be able to build a network that can differentiate between many types of algae and having samples from different resources and different conditions helps the network to be able to work with new data easily. Also making the dataset available publicly can open the field to different research on algae and micro-organisms.

From the publications included in this SLR, the publicly available datasets are very few and some of them are being used in more than one publication, the most commonly used dataset is the WHOI dataset which is being used as a whole dataset or some samples from it in 4 publications from the 12 publications that use the public datasets, the 2nd commonly used dataset is the Kaggle dataset that is used in 3 publications, and finally, the ZooScan dataset is being used in 2 publications.

Table 3 shows a summary of the datasets used in each publication included in the review, the table shows the dataset used, the type of access of the dataset, the size of the dataset, the number of classes, the country of origin where the dataset was collected and finally remarks and comments on the dataset.

Most publications used self-collected datasets and are not available online for public use. Data augmentation was used in most of the publications some of them mentioned the number of images before and after augmentation, while others didn't mention it. The country of origin is mentioned in some publications. The data covered in Table 3 are added to the table and missing data are left blank.

The publications included in this review are reviewed and summarized in Table 3. Some papers referred to the source of the dataset while others just mentioned they used open-access datasets without mentioning any other information about the used data. Figure 6 shows a summary of the type of datasets used in included review papers. The countries of origin of the mentioned datasets are shown in the world map given in Figure 7. The location shows the places where the datasets are collected. In general, the images were collected from many places such as New Zealand, Korea, China, Thailand, Oceans, Spain, the U.S.A, France, etc.

After discussing the nature of the dataset used in each publication used in this SLR and how the datasets are generated and modified to fit the model proposed and the task of algae classification or detection, one important factor that affects the performance of the model is the availability of enough data to train the model such that the training data contains enough different variety of samples for each class. When a network is trained with enough good and diverse data this helps to improve the performance of the network when tested with different data.

Since the splitting and division of the dataset have a great effect on the performance Table 4 shows the dataset splitting and division used to get the training set, testing set, and

TABLE 3. Summary of dataset for algae classification.

No.	Ref.	Year Journal/ Conference	Dataset	Type of Access	Size of Dataset	No. of classes	Country of origin	Preprocessing (Remarks about the dataset)
1	[20]	2020 conference	Collected from the Yangtze River	Limited	1859 images	27 genera 6 classes	P. R. China.	-Dataset is High imbalance -random rotation of images by (+, -) 90 degrees and are cropping images for augmentation
2	[21]	2021 conference	Collected from Suzhou River, Shanghai Baisha River, Qingdao	Limited	1195 images (393 for algae)	Three classes: -Algae -Lotuses -Red Caltrops	Southeast China	-the dataset consists of 393 algae photos, 402 lotuses photos, and 400 red caltrops photos. -Data augmentation is used such as flipping the image, shifting the image, rotating the image, adding noise to the photo -Augmentation was done one time and five times.
3	[22]	2017 conference	videos of underwater pipeline inspections tasks	Limited	41,992 images	Two classes: -Algae -Non-Algae	-	-Data augmentation was employed on the training set, to obtain seven extra samples from each image. -images were collected from (Video frames) in a sliding mode.
4	[23]	2017 conference	Videos of underwater pipeline inspection tasks.	Limited	19,921	Two classes: -Positive -Negative (Algae or Non-Algae)	-	-153 frames extracted from a video. - obtained seven extra samples from each original image were included. -image resizing is used. -to remove noise gaussian filter is applied -Canny edge detector and Hough transform are implemented.
5	[24]	2017 Book Chapter	Collected from Chlorella Ponds.	Limited	400 images	Monitor the Rate of algae growth	-	-20 digital photographs were taken daily in the morning and 20 were taken in the evening for 10 days. applied Filtering techniques, Removed noisy pixel
6	[25]	2022 Journal	four diatom datasets with different background interference degrees are constructed	Limited	3,306 images	8 classes	Provided by the Criminal Science and Technology Department	-the 1st dataset: diatom object is segmented manually, the non-object region is filled by a background of a single grayscale -In the 2nd dataset the non-object region is the background of the original image. -the 3rd dataset: the geometric center of the diatom object located at the center of the image. -the 4th dataset no processing is performed. -the dataset with the partially complex backgrounds and the complex backgrounds are manually Cropped to reduce the interference of the backgrounds
7	[26]	2020 Conference	Collected from Computer vision laboratory UdeA	Open Access with a request	1,680 images	Four Classes	-	- dataset consists of Scendesmus algae with 1,2,4,8 coenobium
8	[27]	2019 Conference	-Collected from various sources	Some open access, others limited access	300 images	Five genera	-Bung Borapet fresh water source, Nakhon Sawan province Khlong kamphuan watershed, Ranong province -Department of Botany,	-conversion of images from RGB to grayscale edge enhancement, Shape, and texture features are used. -The number of images is very limited

TABLE 3. *(Continued.)* **Summary of dataset for algae classification.**

9	[28]	2017 Journal	-WHOI dataset - ZooScan dataset -Kaggle dataset	Open access	28,748	More than 20 categories	Kasetsart University, Thailand -Metropolitan Waterworks Authority -the internet -Woods Hole Harbor water. -Bay of Villefranche-sur-mer, France Straits of Florida	-
10	[29]	2021 Journal	Self-collected SEM images	limited	255	Five species	-The Western and Eastern Mediterranean Sea -The NE Atlantic Ocean	-five duplications of each image in the training set were obtained -changes in brightness, rotation up to 1 degree, and zoom to a maximum of 0.7, horizontal flip.
11	[30]	2021 Journal	11 weir pools Five reservoirs	Open access	469	Segment algae	Korea	-
12	[31]	2020 Conference	NIWA ADIAC	Open access	7092	9 Categories	North and South Islands of New Zealand	-Augmentation was used while training, including flipping and random resized cropping. Convert images to grayscale. -to reduce noise gaussian blur is applied. The threshold applied to binaries the images
13	[32]	2020 Conference	Images collected for red tide algae	Limited access	1800	9 Species	Marine biology laboratory of the Ocean College of Zhejiang University.	-contains about 200 images for each species -Graying and binarization, Morphic operation, Sub-image extraction are applied -shape features, color features, Hu Moment invariants, and GLCM textural features are extracted
14	[33]	2020 Journal	AQUALITAS dataset	Open Access	126 images With 8000 annotated images	80 taxa		Data augmentation rotation and flipping to get bigger datasets and to analyze the influence of samples per class.
15	[34]	2020 Journal	Internet sources and previous phycology studies	Open access	100 images Augmented to 80,000 images	16 classes	-	-
16	[35]	2020 Journal	Collected from Port Canaveral	Limited access	600 images	Specified for Count diatoms in image	U.S.A.	-Data augmentation using random rotation by 90° Color, brightness, and contrast were modified randomly
17	[36]	2020 Journal	Collected from the Geum River and Nakdong River	Limited Access	1250 images	Five classes	South Korea	-
18	[37]	2020 Journal	Pediastrum images	Open Access	80 images	7 species		-images are augmented to 42,000 images
19	[38]	2020 Journal	Obtained from the University of León	Limited Access	126 images	10 taxa	Spain	-Data augmentation rotating, mirroring, and enhancing contrast are applied for each input image for each epoch.
20	[39]	2019 Conference	Plankton images	Open Access	235 images	Five Categories		-

TABLE 3. *(Continued.)* **Summary of dataset for algae classification.**

21	[40]	2019 Conference	pools, lakes, ponds	Limited Access	277 ground images 150 aerial images	Detection Two classes: -Algae -No Algae		-The images are self-collected, obtained from online resources, and generated through artificial simulations.
22	[41]	2019 Conference	Dataset about red tide algae	Limited Access	3500	63 species	The coastal area of South Korea.	-Preprocessing consists of three steps: fixing the size of the image, image rotating, and image normalization
23	[42]	2019 Journal	Collected images of harmful algae	Limited Access	1922	8 genera	South Korea	-data is augmented and then 5790 augmented -augmented is done by mirroring, rotating, and top-down flipping
24	[43]	2018 Conference	WHOI-Plankton dataset	Open Access	3.6 million images	103 classes	-	Shape & Texture Feature Extraction methods are applied
25	[44]	2017 Conference	Collected images for microalgae	Limited Access	29,449 images	19 classes	South Atlantic Ocean	-augmentation applied by rotation, flipping, cropping, and noise addition.
26	[45]	2021 Journal	collected microalgae images using FlowCAM	Limited Access	289,708 images	Two classes	-	-Preprocessing for AlexNet images were converted to grayscale
27	[46]	2021 Journal	Collected images for microalgae	Limited access	Around 42,200 images	Two classes -Algae -Non-Algae	-	-produce a segmentation map then extract features from the map -features such as area, perimeter, circularity, eccentricity, brightness, color intensity ratios
28	[47]	2021 Conference	collected from different open source and past study	Some open access, others limited access	200 images and a total of 12,000 after segmentati on	Four Classes	-	-Data augmentation used such as flipping horizontally and vertically rotating and zooming.
29	[48]	2021 Journal	Most are collected using IFCB, some are obtained from the WHOI plankton dataset	Limited access	108,684 images	112 Classes	Texas Port Aransas Surfside Beach	-Image augmentation of flipping horizontal and vertical, and horizontal shifting of the image -stretching or shrinking an image (unpadded) and padding followed by shrinking (padded) are used to resize images
30	[49]	2021 Journal	Collected freshwater microscopic images	Limited Access	1,114 images	30 Genera	-	-each algal cell image object was labeled manually using a program developed for labeling in this study
31	[50]	2021 Journal	Kaggle Algae cell image	Open Access	7859 algae images and 159 algae genera	11 species of harmful algae 31 species of harmless algae	China	-image augmentation applied such as random rotating, brightness variation, and adding noise.
32	[51]	2018 Conference	ILES Dataset CZECH Dataset	Limited Access	-ILES A 60K images -ILES B 780K unlabeled images -CZECH 167K unlabeled images	Four Classes	-	-Otsu thresholding, image augmentation applied such as mirrored horizontally and vertically, rotation

TABLE 3. *(Continued.)* **Summary of dataset for algae classification.**

33	[52]	2018 Conference	Diatom Dataset	Limited Access	11,000 images	10 Species	-	-
34	[53]	2018 Conference	WHOI-Plankton Dataset	Open Access	-	Five Classes	-	-
35	[54]	2018 Journal	ISIIS Dataset	Limited Access	About 25 million images	108 Classes	The Gulf of Mexico	Normalize contrast, remove noise, segmentation
36	[55]	2018 Journal	SIPPER datasets	Limited Access	DS1: 3,119 DS2: 100,503 DS3: 106,691	Dataset1: 7 classes Dataset2: 52 classes Dataset3: 77 classes	The Gulf of Mexico	Image resizing
37	[56]	2019 Journal	WHOI ZooScan Kaggle	Open Access	WHOI: 6600 ZooScan: 3771 Kaggle: 14374	WHOI: 22 Categories ZooScan: 20 Categories Kaggle: 38 Categories	-	-for the pre-preprocessing step the following four approaches have been applied: gradient, orientation, LBP, and LTP.
38	[57]	2019 Conference	Diatom Dataset	Limited Access	1085 images	14 classes	-	data augmentation applied by Horizontal flip, Vertical flip, and Random rotation between 0∘ and 90∘
39	[58]	2019 Conference	Diatom Dataset	Open Access (Available under request)	126 diatom images with 1446 diatoms	10 taxa	-	-data augmentation image rotations, translations, crops, mirror effects, Gaussian noise, and contrast enhancements
40	[59]	2022 Journal	Collected by Nakdonggang National Institute of Biological Resources	Limited Access	437 images and 1,164 labeled algae	3o Genera	South Korea	-images were resized and rescaled to fit for network
41	[60]	2022 Journal	-Samples were obtained from the AQUALITAS project -Samples were obtained from the DIADIST dataset	Open Access	976 diatom images	14 species	-	-data augmentation applied by geometric transformation, noise injection, GAN, and the proposed model
42	[61]	2022 Journal	- Samples were collected - collected by the main laboratory of Quaid-Azam University Islamabad	Limited Access	400 microscopic algae images	Four species	Pakistan	-data augmentation applied to have 3200 images with 800 images for each class
43	[62]	2022 Journal	Diatom dataset	Open Access with a request	-	110 species	Menne river	-data augmentation applied
44	[63]	2022 Conference	- collected by the main laboratory of Quaid-Azam University Islamabad Pakistan	Limited Access	400 microscopic algae images	4 classes	Pakistan	-traditional and advanced augmentation applied, 800 images per class

TABLE 3. ***(Continued.)*** **Summary of dataset for algae classification.**

45	[64]	2022 Journal	-Kaggle Diatom dataset	Public	2197 images (60% for classificati on, 40% for segmentati on)	68 species	Turkey	-augmentation used on the classification set to get 26,134 images containing diatoms and non-diatoms
46	[65]	2022 Journal	Microscopic dataset	Limited	10,000 images	4 classes	-	-

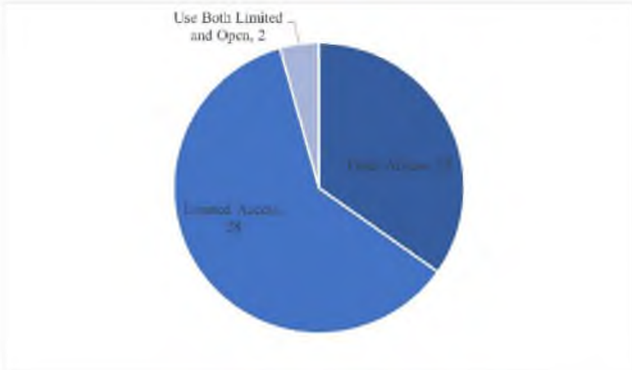

FIGURE 6. **Publications datasets type of access.**

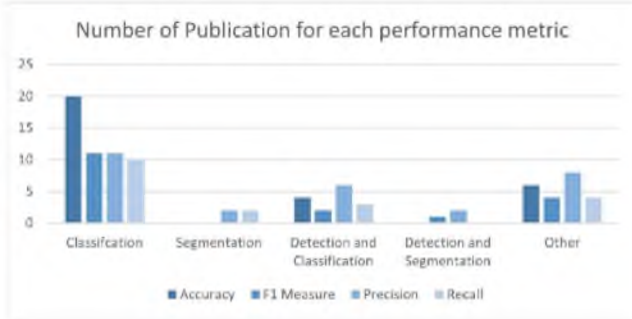

FIGURE 8. **Summary for common performance metric of included publications.**

FIGURE 7. **Distribution of origin of datasets.**

validation set, also it is mentioned if the publication uses cross validation in the dataset while training or not.

Some publications didn't mention the splitting percentage used so they are shown in the table with no percentage. Moreover, the performance of the models used in each publication is shown in Table 4, for some publications testing was applied several times either on the same model but with different amounts of data, i.e. different augmentation sizes on the dataset, while others applied the data on several models and compared their performance. Table 4 shows the best performance.

Some publications used the cross-validation method where cross validation is a technique used to evaluate the stability of the model and assess how well the model performs on unseen data [71]. It is used to overcome the over-fitting problems where the model gives high accuracy on training data and fails to make predictions with high accuracy when it is exposed to new data. Cross validation is beneficial when the data is limited and is a good way to determine which model is considered a good predictor.

The basic and most commonly used type is K-fold cross validation where the data is portioned into equal size K segments of the fold, then K iterations are performed on training and validation where at each iteration a different fold (segment) is held out for validations and the remaining folds are used for learning, the process continues until all folds are used once as test sets then the average of all results is calculated to evaluate the model performance [72].

Table 4 also summarizes the performance of each publication. Each publication presented the result achieved from different perspectives such as Accuracy, F1-Measure, Precision, and recall. Figure 8 shows a summary of the number of publications for each performance metric for each task. For classification tasks accuracy is the most common metric used for the performance evaluation of the model used. The graph is divided into five groups based on the task performed, which are classification only, segmentation only, both detection and classification, both detection and segmentation, and finally the last group with the name other includes publications that perform other tasks or combination of several tasks rather than those mentioned such as localization, recognition, classification, and segmentation, and counting.

Not only having the microalgae dataset is an issue but also there are issues related to pre-processing of the dataset for better classification. As deep learning requires good spatial information for classifying and detecting algae, few researchers working on various pre-processing techniques including image enhancement, data augmentation, and balance strategy which are mentioned in Table 3 that will be discussed in the next sub-sections. All these pre-processing techniques help in reducing network complexity and reaching high accuracy for classification.

1) IMAGE ENHANCEMENT

Since the water samples and the microscopic images of algae are collected from different places, with different conditions, and with different tools and methods, image enhancement techniques have been applied to get better image quality and to highlight the important spatial region of information of an image. For example, image enhancement techniques can remove noise, add noise, sharpen, or brighten an image.

The image enhancement techniques that were used in some of the articles included in this study are image resizing which is used in [22], [23], [48], [55], and [59], filtering techniques to remove noise as used in [24], [31], [32], [36], and [38], contrast enhancement used in [27], [33], and [38], scaling used in [30], padding images used in [31], image cropping to sub-images used in [32]. In Deep Learning, similar methods can be employed as an image enhancement module before inserting it into the DL network.

2) DATA AUGMENTATION AND BALANCE STRATEGY

Since the dataset of microalgae is imbalanced, it has been observed the regular use of data-level imbalance addressing methods in the pre-processing phase. The augmentation of data is used to generate more data to make a balanced class distribution and generate a more comprehensive training set that helps in having a more generalized model and reduces the overfitting of the model [44]. Data augmentation is being used in [20], [21], [22], [31], [33], [34], [35], [37], [38], [42], [44], [47], [48], [50], [51], [57], [58], [60], [61], and [62] such as rotating, flipping, mirroring and other augmentation techniques. Data augmentation is useful in deep learning not only because it increases the size of data but also to improve the performance of the DL model, by making the data rich and sufficient, creating variations in the model, and reducing operational cost [73].

This section discussed the first RQ for this SLR with details about the dataset for each publication, after discussing the dataset it is important to know the models and architectures that this dataset was applied to, and this will be discussed in the next section for RQ2. The second RQ discussed and answered for this SLR is about the algorithm used for each publication this will include deep learning algorithms, CNN, and conventional techniques if used and how those algorithms work, and how they were applied to the datasets discussed in RQ1 and type of training of each network.

B. WHAT LEARNING ALGORITHMS AND DEEP NETWORK ARCHITECTURES ARE APPLIED?

The publications included in this SLR for microalgae classification or detection mainly use supervised machine learning techniques, this is due to having data that is labeled and suitable for supervised techniques [74].

The deep learning network that is employed for algae classification or detection is a convolutional neural network (CNN), some publications represent a framework based on multiple CNN and deep learning architectures as in [31], [33], [36], [45], [52], [53], [56], [59], [60], [61], and [62]. While some publications used traditional machine learning techniques for the classification or the detection of algae as in [22], [27], [28], [32], [39], [41], [58], and [60]. Using multiple techniques helps to show the difference between these techniques and networks and how they can give different performances when applied to the same dataset.

Convolutional neural networks (CNN) are the recent and most used architecture for microalgae classification or detection tasks, it can be grouped into three types which are:

- Pre-trained CNN and transfer learning.
- CNN for classification or detection.
- Hybrid CNN with other techniques [75].

This section reviews the algorithms used for microalgae classification or detection based on the selected literature publications.

We can also see in some architectures the combination of CNN with other machine learning algorithms to accomplish the job of each publication. Table 5 summarizes the method used in each publication and the type of training of the proposed model. Most of the publications that use available deep convolutional neural networks without any changes or modification in the architecture used transfer learning for training the network, while others that used traditional machine learning techniques or modified deep CNN architectures or hybrid models trained the network from scratch as discussed in Table 5.

Most of the publications included in this SLR perform classification tasks more than segmentation or detection, while others choose to perform other tasks such as localization, and recognition, or perform several tasks such as detection and classification together, or detection and segmentation together, Table 6 shows the task performed in each publication. The tasks are divided into 3 categories: classification task segmentation task, or other that may include other tasks or several tasks together.

For the detection task, it can be found with the classification task as it is considered as a baseline function for classification, where before classifying algae in images it first needs to determine whether the image contains algae or not. While in segmentation each object is colored with

TABLE 4. Data division and test performance.

No.	Ref.	Data partitions	Cross Validation	Performance
1	[20]	Training: 80% Testing: 20%	-	the mAP at class level: 81.17% the mAP at genus level: 74.64%
2	[21]	Training Validation Testing	✓	Model 1 Accuracy: 99.16% Model 2 Accuracy: 100% Model 3 Accuracy: 100%
3	[22]	Training: 60% Validation: 20% Testing: 20%	✓ K-fold cross-validation (K=4)	CNN Accuracy: 99.4% MLP Accuracy: 95.7%
4	[23]	Training: 80% Testing: 20%	-	Accuracy: 93.60%
5	[24]	Training Validation Testing	✓	Accuracy: 91.82%
6	[25]	Training: 60% Validation: 20% Testing: 20%	✓	Accuracy: 86.4%
7	[26]	Training: 70% Testing: 30%	-	Accuracy: 95%
8	[27]	Training: 75% Testing: 25%	✓ K-fold cross-validation (K=4)	Accuracy: 91.30%
9	[28]	Training Validation Testing	✓ K-fold cross-validation (K=5)	WHOI dataset Accuracy: 92% ZooScan dataset Accuracy: 88.34% Kaggle dataset Accuracy: 83.67%
10	[29]	Training Validation	✓ K-fold cross-validation (K=4)	Accuracy: 64%
11	[30]	Training: 68% Testing: 32%	-	Precision: 92.5%
12	[31]	Training: 84% Testing: 16%	✓ Leave one strategy cross-validation	Accuracy: 94%
13	[32]	Training Validation Testing	✓	Accuracy: 96%
14	[33]	Training: 83% Validation: 17%	✓ K-fold cross-validation (K=10)	Accuracy for classification: 99.51% Accuracy for detection: 86%
15	[34]	Training and validation: 80% Testing: 20%	✓	Accuracy: 99.97%
16	[35]	Training: 80%% Validation: 20%	✓	F1 score: 82%
17	[36]	Training: 70%% Validation: 30%	✓	Average Precision: 90.22%
18	[37]	Training: 80%% Validation: 20%	✓	Accuracy: 98.45%
19	[38]	Training: 83% Validation: 17%	✓	Average Segmentation Precision: 85%
20	[39]	Training Testing	-	Accuracy: 99.5%
21	[40]	Training: 70% Validation: 20% Testing: 10%	✓	Accuracy: 82%
22	[41]	Training Testing	-	Accuracy: 94.7%
23	[42]	Training: 60% Validation: 20% Testing: 20%	✓	F1 Score: 95%
24	[43]	Training: 91.43% Testing: 8.57%	-	Accuracy: 96.58%
25	[44]	Training: 70% Validation: 30%	✓	Accuracy: 88.59%

TABLE 4. ***(Continued.)*** **Data division and test performance.**

26	[45]	Training: 70% Validation: 15% Testing: 15%	✓	-
27	[46]	Training: 80% Validation: 20%	✓	-
28	[47]	Training: 80% Testing: 20%	-	Accuracy: 99.54%
29	[48]	Training: 80% Validation: 20%	✓	-
30	[49]	Training: 70% Testing: 30%	-	mAP: 81%
31	[50]	Training: 70% Testing: 30%	-	Accuracy: 98%
32	[51]	Training: 80% Testing: 20%	✓ 50% of the training set, training was repeated 10 time	Accuracy: 96.08%
33	[52]	Training Validation	✓ K-fold cross-validation (K=10)	F-measure: 84%
34	[53]	Training Testing	-	Accuracy: 94.98%
35	[54]	Training Testing	-	Average Precision: 90.7%
36	[55]	Training: 70% Validation: 15% Testing: 15%	✓	Accuracy: 98.20%
37	[56]	Training Testing	✓ Two- and five-fold cross-validation	Accuracy: 95.27%
38	[57]	Training: 80% Validation: 10% Testing: 10%	✓	Accuracy: 99.07%
39	[58]	Training Testing	✓ Holdout validation	Average Precision: 73%
40	[59]	Training: 78% Testing: 22%	-	Model 1 mAP: 40.9% Model 2 mAP: 88.8% Model 3 mAP: 84.4% Model 4 mAP: 89.8%
41	[60]	Training: 80% Validation: 10% Testing: 10%	✓ K-fold cross-validation (K=5)	Accuracy: 99.29%
42	[61]	Training: 80% Testing: 20%	-	Model 1 mAP: 75.3% Model 2 mAP: 83.0% Model 3 mAP: 90.1%
43	[62]	Training: 60% Validation: 20% Testing: 20%	-	Model 1 Precision: 78.0% Model 2 Precision: 72.4%
44	[63]	Training: 80% Testing: 20%	-	Model 1 Accuracy: 95.0% Model 2 Accuracy: 96.16% Model 3 Accuracy: 96.35% Model 4 Accuracy: 97.10%
45	[64]	Training: 70% Validation: 15% Testing: 15%	-	Classification accuracy: 99.8% (diatom & non-diatom) Segmentation Precision: 0.924
46	[65]	Training: 80% Validation: 10% Testing: 10%	-	mAP: 0.75

different shades to differentiate between them. Segmentation is mostly used when the image has more than one class, so it is useful in detecting and classifying multiple objects in an image.

Deep learning has various forms and comes from different sources. The two major different types of uncertainty in deep learning are epistemic uncertainty and aleatory uncertainty. Epistemic uncertainty describes the model error and what

(a) (b)

FIGURE 9. Task and techniques applied (a) percentage distribution (b) statistic on different DL techniques from 2017-2022.

the model doesn't know because of lack of experience and because the training data is not appropriate and limited data and knowledge. The epistemic uncertainty can be reduced by giving enough training samples. aleatory uncertainty is the second type of uncertainty it refers to the inherent uncertainty due to the probabilistic variability. It describes the irreducible inherent noise of the observed data. The aleatory uncertainty can't be reduced even by providing more data. The three main sources of uncertainty in machine learning are:

- Noise in data
- imperfect model
- Incomplete coverage of the domain from the dataset perspective that is related to RQ1 of this SLR.

Probability provides the tools and foundation for quantifying and handling uncertainty in machine learning. Some of the effective approaches that help to deal with uncertainty in machine learning are model calibration, Bayesian inference, and using external sources. Model calibration takes place by adjusting the model confidence to be more robust. Bayesian inference uses special statistical machine learning models that can incorporate uncertainty in their predictions. Finally using external scores and metrics to better estimate the model confidence for prediction.

Deep learning models have been proved to achieve interesting performance and high accuracy in several tasks recently. But they have a poor performance in quantifying the uncertainty of predictions. The accurate prediction for the model is not enough for many real-world applications, the model must also be able to quantify the uncertainty of the prediction. Where sometimes depending on the application uncertainty is more important than precision. Uncertainty means working with incomplete or imperfect data. Uncertainty has various forms and comes from different sources.

A summary of the tasks is shown in Figure 9-a where it can be seen that most publications either used classification only or used other techniques that may include detection with segmentation, classification and segmentation, detection and classification and others also Figure 9-b shows the yearly distribution of each task. After discussing the datasets in RQ1 and discussing the methods and tasks done on those datasets in RQ2, RQ3 will discuss the challenges, and issues for each publication and review the future direction for each work.

C. WHAT ARE THE CHALLENGES, ISSUES, AND FUTURE DIRECTIONS OF THIS WORK?

The third RQ for the SLR is about challenges and issues that faced the authors of each publication while performing the proposed task, also future directions are discussed for each publication if mentioned. Table 7 tabulated all the information needed to cover RQ3. The common issues on this RQ are pertinent to the quality of classification that comes from the small amount of dataset available for algae. Commonly, as mentioned in RQ1, the dataset needs to be augmented to have a large dataset that is required by deep learning networks. Another issue is that the work done is limited to classifying only a small number of different classes of microalgae, beside those issues is the issue that most images collected are with a low resolution which affects the performance of the network to perform the target task.

D. DISCUSSION

1) LEARNING OUTCOMES FROM THE RQS

The review of the RQs shows that deep learning, machine learning, and computer vision techniques have made a strong presence in microalgae classification and detection in a short period of only six years. A big number of research covering all aspects of microalgae classification or detection or segmentation with machine learning and deep learning has been contributing. We can find simple feature extractors, simple and complex classifiers, a combination of various architectures, and learning algorithms.

2) GENERAL DISCUSSION ON ADDRESSING THE SPECIFIC ISSUES

The studies presented in this review tried to solve some challenges. On the top of the list is the limited number of datasets

TABLE 5. Publication methods and training type.

No.	Ref.	Method	Training Type
1	[20]	Framework Extended from Faster R-CNN	Transfer Learning (ResNet-50 based FPN network pre-trained is applied to initialize the proposed framework)
2	[21]	Modified CNN Models and Vision Transformer	Transfer Learning with improvements
3	[22]	CNN and MLP	Trained From Scratch
4	[23]	Neural network and a wavelet-based feature	Trained From Scratch
5	[24]	ANN and CNN	Trained From Scratch
6	[25]	The deep learning framework is constructed	Trained From Scratch
7	[26]	AlexNet	Trained From Scratch
8	[27]	support vector classifier	Trained From Scratch
9	[28]	multiple kernel learning (MKL)	Trained From Scratch
10	[29]	Convolutional Neural Networks (CNNs) based on VGG16	fine-tuning pre-trained
11	[30]	Weighted Mask R-CNN	Modified + Transfer Learning
12	[31]	Resnet-18, Resnet-50, AlexNet and Inception v3	Transfer Learning
13	[32]	Logistic Regression (LR), Support Vector Machine (SVM), and Extreme Gradient Boosting (XGBoost)	Trained From Scratch
14	[33]	YOLO network and AlexNet network. CNN for semantic segmentation (SegNet) CNN for instance segmentation (Mask-R-CNN)	Transfer Learning
15	[34]	ResNeXt CNN	Modified Transfer Learning
16	[35]	fully convolutional neural network similar to YOLO	Trained From Scratch
17	[36]	Fast (R-CNN) and convolutional neural network (CNN).	Transfer learning and Trained from Scratch
18	[37]	ResNeXt CNN	Modified Transfer Learning
19	[38]	SegNet and Mask-RCNN	Pre-Trained Transfer Learning
20	[39]	Feature Extraction models: Inception v3, VGG-16, VGG-19 Classification algorithms: Convolution Neural Network, Logistic Regression, Support Vector Machine, and k-Nearest Neighbors.	Fine-tuned Transfer Learning
21	[40]	Deep learning models: Faster R-CNN, Single Shot Detector (SSD), and Region-based Fully Convolutional Networks (R-FCN)	Pre-Trained Transfer Learning
22	[41]	Image recognition methods: LHANMF, PCA, NB, NN, SVM, B+SVM, SVDD+SVM, SVM+FCM, PCA+RE, and RNMF	Trained From Scratch
23	[42]	Neural architecture search (NAS), an automatic approach for the design of artificial neural networks (ANN), is used to automatically examine possible CNN architectures and yield a more accurate CNN architecture for algal classification.	Trained From Scratch
24	[43]	hybrid convolutional neural network using AlexNet	Modified + trained from scratch
25	[44]	CNN	Trained From Scratch
26	[45]	CNN, AlexNet	CNN trained from scratch. AlexNet pre-trained
27	[46]	CNN based on densenet121 architecture	Multiple architectures trained from scratch
28	[47]	Modified AlexNet CNN model	Trained from Scratch
29	[48]	Ensemble CNN classifier and random forest classifier	Trained from Scratch
30	[49]	YOLOv3 deep learning model	Pre-Trained
31	[50]	CNN (lexNet, VGG16, GoogLeNet, ResNet50, and MobileNetV2)	Pre-Trained transfer learning
32	[51]	CNN	Trained from Scratch
33	[52]	RCNN, YOLO	Pre-trained
34	[53]	CNN CIFAR10, VGG16, AlexNet	Pre-trained Transfer Learning
35	[54]	CNN	Trained from Scratch
36	[55]	CNN	Trained From Scratch
37	[56]	deep learning: AlexNet, GoogleNet, InceptionV3, VGGNet, ResNet, DenseNet, SqueezeNet	Fine-tuning and transfer learning
38	[57]	Deep learning: ResNet18, AlexNet, VGG11, SqueezeNet1.0, DenseNet121, and InceptionV3	Transfer learning as a fine-tuning strategy
39	[58]	Classical techniques Viola-Jones, SCIRD Deep learning: YOLO, SegNet	Trained From Scratch

TABLE 5. ***(Continued.)*** **Publication methods and training type.**

40	[59]	YOLO V3, YOLO V3-tiny. YOLO V4, YOLO V4-tiny.	Trained From Scratch
41	[60]	CNN architectures: ResNet18, AlexNet, VGG11, SqueezeNet1.0, DenseNet121, and InceptionV3.	Transfer Learning
42	[61]	YOLO V3, YOLO V4, YOLO V5	Trained From Scratch
43	[62]	Mask R-CNN U-Net	Transfer Learning
44	[63]	VGG-16, AlexNet, GoogleNet, ResNet18	Transfer Learning
45	[64]	AlexNet, ResNet18, VGG16	Transfer Learning
46	[65]	Algae-Yolo	Modified Transfer Learning

TABLE 6. **Publication main task on microalgae images.**

No	Reference	Year	Classification	Segmentation	Other
1	[20]	2020			Detection and classification
2	[21]	2021	✓		
3	[22]	2017			Detection and classification
4	[23]	2017			Detection and classification
5	[24]	2017	✓		
6	[25]	2022			Localization and Recognition
7	[26]	2020	✓		
8	[27]	2019			Classification and segmentation
9	[28]	2017	✓		
10	[29]	2021	✓		
11	[30]	2021		✓	
12	[31]	2020	✓		
13	[32]	2020			Classification and Segmentation
14	[33]	2020			Detection and Classification
15	[34]	2020	✓		
16	[35]	2020			Detection and counting
17	[36]	2020			Classification and counting
18	[37]	2020	✓		
19	[38]	2020			Segmentation, Detection, and Counting
20	[39]	2019	✓		
21	[40]	2019			Classification and detection
22	[41]	2019			Recognition
23	[42]	2019	✓		
24	[43]	2018	✓		
25	[44]	2017	✓		
26	[45]	2021	✓		
27	[46]	2021	✓		
28	[47]	2021	✓		
29	[48]	2021	✓		
30	[49]	2021			Detection and Classification
31	[50]	2021	✓		
32	[51]	2018	✓		
33	[52]	2018			Detection and classification
34	[53]	2018	✓		
35	[54]	2018	✓		
36	[55]	2018	✓		
37	[56]	2019	✓		
38	[57]	2019	✓		
39	[58]	2019			Detection and segmentation
40	[59]	2022			Detection
41	[60]	2022	✓		
42	[61]	2022			Detection and classification
43	[62]	2022		✓	
44	[63]	2022	✓		
45	[64]	2022			Classification and segmentation
46	[65]	2022			Detection

and images available for algae classification for research and development. Imbalance class distribution of data is a major issue also the lack of diversity of algae classes in a single dataset. The need to use machine learning and deep learning

TABLE 7. Challenges, issues, and future direction.

No	Ref.	Challenges, Issues, and Future Direction	problem to be solved, limitation on current work, a combination of DL with morphology
1	[20]	The performance of the proposed network is affected by the following problems: 1-undetected algae (transparent and blended into the background). 2-occlusion of algae (overlapping of algae with other non-algae objects). 3- wrong classification (inter-class similarity). **Future work:** -trying more image preprocessing and post processing techniques. -implement 3D CNN with other biological features for performance enhancement.	-the main task of the publication is to make algae classification based on the gene and to detect algae using large-scale colored microscopic dataset.
2	[21]	-Collecting the pictures manually is one of the biggest problems that faced this work, where many photos are highly similar and only a few sites were used to take photos due to geographical limitations. - The use of augmentation improved the situation in some ways, but it cannot simply replace the sunlight and other sources of noise. **Future work:** -collect more diverse data, and more research needs to be done about how many times to perform and apply augmentation.	-determining whether the water plants are algae of a landscape by auto-system is the main target of this work. -vision transformer was applied for the first time for the algae classification task.
3	[22]	-objects that are like algae lead to a high false-positive ratio. one of the problems is to improve the accuracy of classification it has a cost in terms of increased processor runtime. **Future work:** Applying a deep neural network based on CNNs to the recognition of several underwater pipeline events other than algae.	-this work proposed a vision inspection system based on deep learning and computer vision algorithms.
4	[23]	-the main problem is that the pipelines and the algae sometimes have similar textures.	-the main task of this work is to detect algae in underwater pipelines in an automatic video processing context.
5	[24]	-classification and identification of algae automatically sometimes is difficult due to some factors such as the size and shape change with the climatic changes, and the existence of other microbes. the significant similarities between classes make it a complicated task to build up a system for measuring algae growth.	-the main target is to design a tool to assist the experts to measure the growth of chlorella algae.
6	[25]	-the main problem of this work is that the process of collecting images for diatoms is long-term and hard work. Also, the background may include contents that may have certain similarities with diatoms, such as structure and texture. **Future work:** -get more images for diatoms to expand the scale of the dataset.	-this work proposed a diatom recognition and localization framework based on the deep learning network.
7	[26]	-the algae classification tasks have the problem of unavailable datasets. Also, in this work, the focus was given to handcrafted feature methods. **Future work:** to make inter-class classification of other species of algae.	-an automatic system for micro-algae classification is proposed in this work.
8	[27]	-the main issue is the limited availability of the image dataset. **Future work:** to apply in Real-time System, and to make predictions of the gene of the algae not only the class.	-this work proposes a new skeleton-based shape descriptor to alleviate an ambiguity caused by multiple morphologies of filamentous forms of algae in the classification process.
9	[28]	-the main problem is the imbalanced datasets, plankton is very sensitive to environmental changes, and most techniques are created for a particular imaging tool and only cover a small taxonomic range. **Future work:** solve the problem of the ability to work well with imbalanced datasets, and build an end-to-end learning system with very less labeled data.	-this work's main task is to develop an extensive plankton classification system.
10	[29]	-Variable sample orientation should be avoided carefully, and the collection of SEM images should be carried out on longitudinal sections. **Future work:** -getting a wider dataset to enhance the model accuracy and to guarantee the reproducibility of the method.	-this work presented a new automated classification and identification tool for coralline algae diagnosis.
11	[30]	**Future work**: -Exploit cutting-edge network architectures and modules in improving accuracy and accelerating computational speed.	-the weighted Mask R-CNN is proposed.
12	[31]	-The main limitation is the number of images that exist combined with the considerable variation in each morphology classification. **Future work:** -to get more labeled training images and create larger datasets. -trying a semi-supervised approach to utilize the unlabeled training data and employing deep learning methods in the detection and classification of multiple diatoms.	- This paper proposes a method to make diatom identification automatically.
13	[32]	-The main limitation of this study is the misclassifying of red tide algae that have similar features based on feature extraction methods where the system reliability is generally dependent on the properties of the image. **Future work:** -getting more species of algae and more images to use deep learning for classification and recognizing red tide algae. Also, make the system become more generalization, robust, and faster.	- The main objective of this work is to construct a color microscopic image dataset of red tide algae and vision-based automated red tide recognition and classification system.

TABLE 7. *(Continued.)* **Challenges, issues, and future direction.**

14	[33]	-the problem faced in this work is that the main controller (Intel NUC) computation power is not enough power to deal with training and inference with AlexNet. **Future work:** -propose more precise algorithms for segmentation to reduce false positives and false negatives.	- This work demonstrates the feasibility of a low-cost automatic platform for digital microscopy to assist in challenging time-consuming tasks.
15	[34]	**Future work:** -enlarge the dataset to include more classes of algae for classification tasks and test the proposed models on the other dataset to make a further evaluation of the model performance.	-this work aims at designing an automatic system for the identification and classification of algae to reduce time and dependency on experts for algae.
16	[35]	-the problem of detecting and counting diatoms is a challenging problem due to the lack of analytical tools. **Future work:** Increase the number of training images with unseen diatoms to enhance the precision of the network.	-a fully convolutional neural network for detecting diatoms is implemented.
17	[36]	**Future work:** consider multiple layers of the Microcystis colonies to improve the cell-count accuracy.	-deep learning network for classifying and quantifying algae is proposed in this work.
18	[37]	**Future work:** to develop a highly sensitive computer-based system for algae identification.	-
19	[38]	-The performance of the detection step limits the performance of the segmentation. **Future work:** improve detection in mask RCNN and continue working on instance segmentation approaches.	-this work uses deep learning to predict the pixels that belong to the algae.
20	[39]	-the lack of datasets that fit the scope of this study in the main issue of this work,	-an automatic framework is proposed in this work for the classification of plankton.
21	[40]	**Future work:** developing a larger dataset to improve performance.	-this paper developed a computer vision algorithm that can detect and locate algae in water bodies.
22	[41]	-it is difficult to recognize harmful algae images because there are over 200 species of algae in the world that have different sizes and features. **Future work**: more research is needed on red tide as damage to fisheries due to red tide occurs yearly in coastal areas of South Korea.	-
23	[42]	**Future work:** increase the number of images of microscopic algae with different species of algae. Extend the possible application of deep learning techniques as a novel method for algal bloom monitoring, making consideration of microalgae colonies. Further extension on developing algae image libraries with more algal species in various field sites would improve the applicability of the model in real-world simulations.	-Algal monitoring and classification using Conventional microscopic methods have been most widely used but such approaches are time-consuming and labor-intensive. - an automatic approach for the design of artificial neural networks called neural architecture search, is used to find the best CNN model for the classification of algae. - suggest the algal image analysis framework using machine learning.
24	[43]	-Serious imbalance problem of the dataset. **Future work:** classifying the plankton effectively on an unbalanced dataset.	-an effective plankton features extraction method followed by an end-to-end hybrid convolution neural network is proposed for plankton classification.
25	[44]	**Future work:** expand the dataset to get better performance and to make a classification for a greater number of classes of algae.	-this work proposes a CNN (Convolutional Neural Network) to classify the images extracted for the microalgae.
26	[45]	**Future work:** extend the network by using more species and samples in different conditions.	-
27	[46]	**Future work:** get more data that can help to distinguish the effects of various contaminants on the algae.	-
28	[47]	-the limited size of data is the main issue for this work. **Future work:** add more algae groups for the identification and categorization.	-The main goal of this work is to solve the problem of identification and classification of different species
29	[48]	-obtaining enough images for each class was not possible due to having uncommon or rare species.	-this work presents and updates the automated early warning system.
30	[49]	**Future work:** increase input data with several characteristics to improve model performance.	-automatic identification and classification of algae images using a deep learning model is proposed in this work.

TABLE 7. *(Continued.)* **Challenges, issues, and future direction.**

31	[50]	The main problem is that the number of collected images of different algae genera is highly unbalanced. **Future work:** standard algae dataset will be leveraged to ensure the consistency of the samples in the experiments.	-
32	[51]	One of the major challenges is the need for large, manually labeled training data.	-this work proposes a classification system for zooplankton classification that is robust against the background noise in images.
33	[52]	-the problem facing this work is the overlapping regions for diatoms in an image. **Future work:** increase the performance of the detection task by parameter tuning, and processing.	-In this work, both detection and classification of 100 taxa have been done. -Extensive process of data collecting, labeling, and processing has been performed.
34	[53]	-ConvNets' drawback is that it can make recognition only for large classes and classifying imbalanced datasets is challenging. **Future work:** use different techniques such as clustering to get dense deep features.	-this work proposes a transferred parallel model to overcome the problem of data imbalance.
35	[54]	-one of the challenges in this work is collecting images from 40h of imaging, 10 TB data then filtering the images.	-
36	[55]	-the problems faced in this work are the low quality of the images, the high level of noise, deformation, and occlusion of plankton objects is challenging. **Future work:** -Extend the work by including Hybrid CNN, and perform comparative assessment on multiple large scale color image datasets.	-this work proposes an intelligent machine learning system built on convolutional neural networks (CNN) for plankton image classification.
37	[56]	**Future work:** evaluate different strategies for layer selection for transfer learning and evaluate other preprocessing methods.	-This work shows how to combine different CNNs.
38	[57]	-the main problem is that some classes have fewer samples.	-This work proposes deep learning using transfer learning and fine tuning for diatom classification
39	[58]	**Future work:** complete work on the complex problem of diatom identification, add post-processing techniques to improve performance, and explore new architectures for instance segmentation.	-this work makes a comparison between classical methods and deep learning methods in segmentation and identification.
40	[59]	**Future work:** the results of this study provide a useful perspective to improve the practical applicability of the object detection model.	-this work developed four YOLO models for algae cell detection.
41	[60]	-the problem with this work is that available datasets are too small and not suitable to train deep learning models from scratch.	-this work proposes a new data augmentation method by combining two samples.
42	[61]	**Future work:** apply new models, such as RetinaNet, by modifying the model architecture for more precision, also adding a greater number of real-world pictures.	-this work proposed a novel model for the detection and classification of algae species by merging the two approaches.
43	[62]	-large slide scans need to be subdivided into small images (tiles) to apply a segmentation model to them. - Giga-pixel-sized images are too large to be directly fed into typical deep learning-based segmentation models.	-This work applied deep learning-based segmentation methods to gigapixel-sized, high-resolution scans of diatom slides with a realistically cluttered background.
44	[63]	**Future work:** employing Yolo4 and Yolo5 to detect algae from microscopic images, and to do the same work for video or real-time streaming video.	-the main task of this work is to make use of Dc-GAN to overcome the deficiency of image data.
45	[64]	**Future work:** Evaluating the contributions of different edge detection methods and CNNs.	-a new and effective model for the automatic segmentation of diatoms based on image processing and deep learning algorithms is proposed.
46	[65]	**Future work:** make an expansion for the dataset, and enlarge the species of single-celled algae.	-

techniques to solve the problem of manual classification as it is a highly tedious task, labor-intensive, time-consuming, and expensive task.

Moreover, microorganism analysis such as done is done traditionally by chemical, physical, molecular biological, and morphological methods. Those methods suffer from the need for expensive equipment, a long time, and can sometimes cause secondary pollution.

To solve those problems image analysis techniques using multiple artificial intelligence approaches, such as machine vision, pattern recognition, and machine learning algorithms are used to support a more clear, cheap, and more rapid way for microorganism analysis tasks.

VI. CONCLUSION AND FUTURE RECOMMENDATIONS

Algae have an important role in many aspects and activities of life. They have a great effect on the environment, so they attract a big interest in studying and research. The review is based on the publications in several journals and conferences in the period 2017-2022. As mentioned earlier, this SLR only focuses on microscopic images, Deep learning techniques without highlighting the use of another conventional methods such as image processing and machine learning technique. Also, the focus is only on algae classification which does not cover the other type of microorganisms such as bacteria, fungi, and protozoa. Also, this review didn't cover the development of techniques over time, it only focused on new research since 2017 and didn't cover any earlier publications, since microorganisms play a very important role in life and algae are not the only micro-organism that exists, machine learning and deep learning are being used to make detection and classification of other micro-organisms such as bacteria and fungi. They have things in common between each other and some characteristics that are different from each other which make differentiating between them using machine learning and obtaining a large enough dataset with enough samples a challenging task. When taking a water sample and creating a microscopic images dataset there is a possibility to find other micro-organisms in the water sample rather than algae, such as bacteria, and fungi. It is important to determine the type of microalgae that exists in the image. Also, deep learning algorithms can't determine the difference between them if it is not trained on bacteria or fungi. This can lead to classifying the image into one of the types of algae even if it doesn't relate to algae.

A. CONCLUSION

This SLR is concluded by summarizing the findings and giving some future directions. The publications included in this SLR have employed various deep learning and machine learning algorithms and architectures, depending on the scope of the research and the availability of data. Every paper investigated some aspects of algae classification or detection using ML and deep learning. General issues have been addressed on classification problems, class imbalance, data unavailability, feature extraction, data augmentation, and preprocessing.

P1 – RQ1 – Dataset
P2 – RQ2 – Techniques
P3 – RQ3 - Challenges

This SLR shows a range of learning algorithms such as transfer learning, hybrid model, and training from scratch. The types of deep network architectures such as various kinds of CNN architectures. The use of pre-trained networks through transfer learning has also been explored widely and proved to enhance the performance of networks. A combination of multiple deep learning algorithms and other machine learning techniques was investigated in some studies. The fusion of deep algorithms with other machine learning and image-processing techniques was also promising.

This SLR is limited to publications that use deep learning algorithms, or a combination between deep learning and classical machine learning algorithms for the task of classification or detection of algae from microscopic images. It doesn't include publications that use radar images, or satellite images. Also, this SLR didn't cover publications that use other methods rather than deep learning and machine learning such as chemical reactions on water samples, or hardware-based systems that require hardware development or are based on IoT.

This SLR will be beneficial to researchers due to the detailed analysis and comprehensive overview of deep algorithms and machine learning techniques applied in the algae image classification, detection, and identification field. Focusing on designing a deep classifier for the classification of a huge number of algae classes and obtaining a diverse dataset and considering the class imbalance of the data.

B. FUTURE DIRECTIONS AND RECOMMENDATION

Based on the findings of this SLR, the following directions should be focused for further contribution to the field:

1) Providing large, diverse, high-resolution data for research purposes. Accurately labeled data for the training of deep networks is a must for exact feature learning.
2) More imbalance management methods should be examined to solve this problem.
3) More attention should be given to evaluating network parameters, the number of layers, activation and loss functions, and kernel and stride size.
4) Fusion of deep learning networks and traditional classification techniques and transfer learning have shown better performance and need to be investigated more.
5) Efficient learning algorithms should be developed to reduce training time, memory, and processing resources.

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DINA M. MADKOUR received the M.S. degree in computer engineering from Arab Academy for Science and Technology and Maritime Transport (AASTMT), Cairo, Egypt, in 2020. She is currently pursuing the Ph.D. degree with the Malaysia-Japan International Institute of Technology, Universiti Teknologi Malaysia, Kuala Lumpur, Malaysia. Her research interests include image classification and recognition using deep learning algorithms, machine learning, and image processing.

MOHD IBRAHIM SHAPIAI (Member, IEEE) received the M.Eng. degree from the University of York, U.K., in 2007, and the Ph.D. degree in machine learning from Universiti Teknologi Malaysia, in 2013. From March 2010 to April 2010, he was a Visiting Researcher with the Graduate School of Information, Production and Systems, Waseda University, Japan, under the supervision of Dr. Junzo Watada and the Faculty of Engineering, Leeds University, U.K., from June 2012 to July 2012, under the supervision of Dr. Vassili Toropov. He is currently a Senior Lecturer with Universiti Teknologi Malaysia and a Researcher with the Center of Artificial Intelligence and Robotics (CAIRO). He has been appointed as a certified NVIDIA deep learning instructor. His research interests include artificial intelligence, machine learning, brain–computer interface, and swarm intelligence.

SHAZA EVA MOHAMAD received the Bachelor of Science degree (Hons.) in biochemistry, in 1997, the Master of Biotechnology degree from the University of Malaya, in 2000, and the Doctor of Philosophy degree in biology and in morphine biocatalysis from the University of York, U.K. She is affiliated with the Department of Chemical and Environmental Engineering, Malaysia-Japan International Institute of Technology (MJIIT), UTM Kuala Lumpur, where she is currently a Lecturer. She continued her postdoctoral study with MJIIT for two years working on enzymes associated with lignocellulosic degradation. She holds many administrative positions which include the Research Manager, the Head of the Department, and currently the Quality and Strategy Manager of UTM. She is also attached to Tokyo City University as a Visiting Lecturer and has strong collaborations with many Japanese universities which include the University of Tsukuba, Tokyo City University, and has several MOUs signed including a recent one which will be with Euglena Ltd., Japan. She has numerous publications within the specialty and published in reputed national and international peer-reviewed journals. She is also actively associated with different national and international societies. She is also a member of the Algae Biomass Research Laboratory, MJIIT. Her research interests include environmental biotechnology focusing on the utilization of microalgae to solve environmental issues and involved in looking at bioproducts such as omega 3, astaxanthin, and biopolymer from microalgae.

HESHAM HAMDY ALY received the Ph.D. degree from Staffordshire University, U.K., in 2019. He is currently an Assistant Professor with the Electronics and Communication Engineering Department, Arab Academy for Science and Technology and Maritime Transport (AASTMT). His research interests include implementing AI concepts on software and hardware for smart city applications based on the IoT systems.

ZOOL HILMI ISMAIL (Senior Member, IEEE) received the B.Eng. and M.Eng. degrees in mechatronics engineering from Universiti Teknologi Malaysia, Skudai, Johor, Malaysia, in 2005 and 2007, respectively, and the Ph.D. degree in electrical engineering from Heriot-Watt University, Edinburgh, U.K., in 2011. He was appointed as a Senior Lecturer with Universiti Teknologi Malaysia (UTM), Kuala Lumpur, in 2011. He was also appointed as a Visiting Researcher with Kyoto University and the Jordan University of Science and Technology, in 2014 and 2016, respectively. He is currently a Research Member of the Malaysia-Japan International Institute of Technology.

MOHD ZAMRI IBRAHIM received the B.Eng. and M.Eng. degrees from Universiti Teknologi Malaysia, Malaysia, and the Ph.D. degree from Loughborough University, U.K. He is currently a Senior Lecturer with the Faculty of Electrical and Electronics Engineering, University Malaysia Pahang, Malaysia. His research interests include computer vision, plasma science, embedded system programming, brain–computer interaction, image processing, intelligent systems, and speech recognition.