Ontology-Assisted Expert System for Algae Identification With Certainty Factors

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ABSTRACT Harmful algal blooms (HABs) are one of nature's responses to nutrient enrichment in aquatic systems and increasingly occur in coastal waters, such as in Lampung Bay and Jakarta Bay, Indonesia. HABs present environmental and fisheries management challenges due to their unpredictability, spatial coverage, and detrimental health effects on coastal organisms, including humans. Here, an automated algae species identification system assisted and validated by expert judgment was proposed. The system used ontology as guidance to determine the species of algae and certainty factors to indicate the level of confidence of the experts when providing a statement or judgment for a particular object or event under consideration. The system was tested to identify 60 samples using 51 predetermined algal characteristics. The tests were narrowed down to the 20 most common HAB-causing algae types found in the study sites and compared with identification by experts. The results showed that the system successfully identified the test data with an accuracy of 73.33%. The system also had a high agreement (above 79.75%) with the identification performed by experts on six algae species. Further improvement of the system's accuracy could facilitate its use as an alternative tool in rapid algal identification or part of an early warning system for HABs.

INDEX TERMS Harmful algal bloom, algae identification, ontology, certainty factor, expert system.

I. INTRODUCTION

Algal blooms and red tides have become common in many saline or freshwater systems worldwide, including Indonesia. Both are considered phenomena in which one or more algae/phytoplankton increase rapidly in the water column. The bloom takes on a red or brown color depending on the pigment contained in the phytoplankton [1]. Some causative red tide species are harmful and produce toxins that can directly kill the organism affected or be transferred through the food web chain from which they retain the name harmful algal blooms or HABs [2]. In addition to toxicity, HABs can also cause respiratory damage to aquatic organisms due to the buildup of algae or their remains in the respiratory system and suffocating hypoxic conditions.

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HABs have become a crucial environmental issue in the last decade, particularly for aquaculture industries, due to their impact on fish culture. Between 1990 and 2015, at least 23 cases of HABs were recorded in Indonesian waters distributed from the Java Sea, Jakarta Bay, Ambon Bay, Lampung Bay, and West Sumatera [3]. However, despite HABs being frequently reported by the media, research institutions, and government, HAB prevention or efficient mitigation to avoid or reduce losses to fish farmers or mass fish mortality has yet to be seen.

The outbreak of HABs is usually related to changes in environmental conditions. Some physical and chemical water parameters induce the rapid growth of HAB species. Some scientists argue that the apparent increase in harmful blooms is strongly linked to eutrophication in aquatic systems [4]. In addition, enrichment provides a vast quantity of nutrients needed by phytoplankton to grow. Therefore, detecting

changes in environmental conditions could be used as an early warning system for HAB prevention or mitigation.

Furthermore, identifying the harmful impacts of HABs is another mitigation approach. For example, various studies have reported the detrimental effects of cyanobacteria (blue–green algae), predominantly found in eutrophic fresh and brackish waters, on aquatic organisms. In addition, some cyanobacteria species produce microcystins, a group of chemically stable cyclic peptide toxins responsible for poisoning cases in animals and humans [5]. Therefore, knowledge of the characteristics of the abundance and poisoning potential of algae to other living organisms will provide critical information to prevent HABs or mitigate their effects successfully.

Various species of algae have been identified to cause HABs. At least 32 [6], 37 [7], and 28 [8] causative species of algae were reported to cause HAB events in the Yellow Sea, South Chinese Sea (SCS), and Southern SCS, respectively. However, some causative species of HABs are still unidentified or at least debated for their identification accuracies [8]. As such, studies on increasing the accuracy and rapid identification of HAB-caused species have been proposed. For example, [9] developed a framework for automatic identification for one species of algae, namely, *Neomeris vanbosseae M. A. Howe* (NVH), which belongs to the Chlorophyta division. In another study, [10] proposed morphological processing and fluorescence imaging for phytoplankton identification. The study utilized a database of the shape of each alga. Similarly, [11] developed a novel multitarget deep learning framework for algal detection and classification. The study collected a large-scale colored microscopic algae dataset and applied extensive identification experiments based on the dataset. Finally, [12] explained a critical development direction for algae classification and determination based on image analysis of biological-morphological differences. However, this study had to address some challenges, such as the high degree of sample imbalance and the difficulty of formalizing the description of local physiological features.

These previous studies relied on identifying algae species based on image analysis and required large datasets processed using machine learning (ML) techniques. An ML system focuses on statistical modeling, which entails creating a recognition model using the existing training data and then using that model to infer conclusions from new observations. For example, in a support vector machine (SVM) or neural network (NN), the modeling might be made up of differentiable parameters such as weights and biases. To minimize an error/cost function, systems are usually optimized using gradient descent-based optimization methods. This optimization technique achieves a minimal error surface. Nevertheless, the result might not be easy to explain, particularly in artificial neural network-based systems. The final result is a functional system for inference with no explanation, which is problematic in some circumstances [13]. For example, a study by [14] demonstrated that the SVM performed poorly when inferencing outside its training set. Furthermore, SVM and

NN require large datasets of hundreds or thousands of images, which bears a high collection cost.

A type of artificial intelligence (AI), the knowledge-based system (KBS), offers a better solution that SVM and NN lack thereof. The KBS uses rules to perform induction and draws a judgment based on facts or knowledge and rules. The drawback of KBS is in generating a knowledge base (KB), which may be time-consuming [15]. However, the model's advantage is that it provides more information on the reason. The KB serves as ground truth, which can be used for various purposes, such as building a faceted search [16] or even a knowledge-based chatbot [17]. Furthermore, the system can explain its logical ''thinking'' process and why it reached that particular conclusion. To the best of our knowledge, this study is the first to identify algal species based on their morphology using KBS in the form of an ontology-assisted expert system coupled with certainty factors.

Currently, most laboratories use labor-intensive manual identification techniques by comparing the observed algal cell morphology using a light microscope with the closest resembling images in plankton printed books or electronic databases. The accuracy of this manual identification process varies depending on the analyst's level of expertise and experience. The method is also tedious and time-consuming due to a one-by-one comparison of morphological characteristics.

An algal bloom outbreak does not suddenly occur. When algae blooms do occur, the growth rate of algae increases rapidly. However, observable signs of environmental precursors and algal bloom developmental stages can be easily recognized, such as gradually changing watercolor. By determining the causative algal bloom species as early as possible before reaching the population peak, the negative impacts of algal blooms, mainly harmful ones, can be prevented or mitigated. The development of a rapid identification system is primarily needed to shorten the algae identification process in the laboratory. Rapid species identification results can allow managers to make right- and on-time decisions, particularly in the mariculture industry. Therefore, an expert system was proposed to assist researchers and laboratory technicians in rapidly identifying algae based on their morphological characteristics. The system uses an ontology to guide the identification process in determining the type of algae coupled with a certainty factor indicating its confidence level.

The rest of the paper is organized as follows. First, in Section II, we describe the data and the research methodology. Then, we explain our findings, including the results and the discussions in Section III and Section IV, respectively. Finally, the conclusion and future works are given in Section V.

II. MATERIALS AND METHODS
This section describes the materials and methods used in this research, including the study sites and data, knowledge base, inference engine, dialog interface, and the design of the experiment.
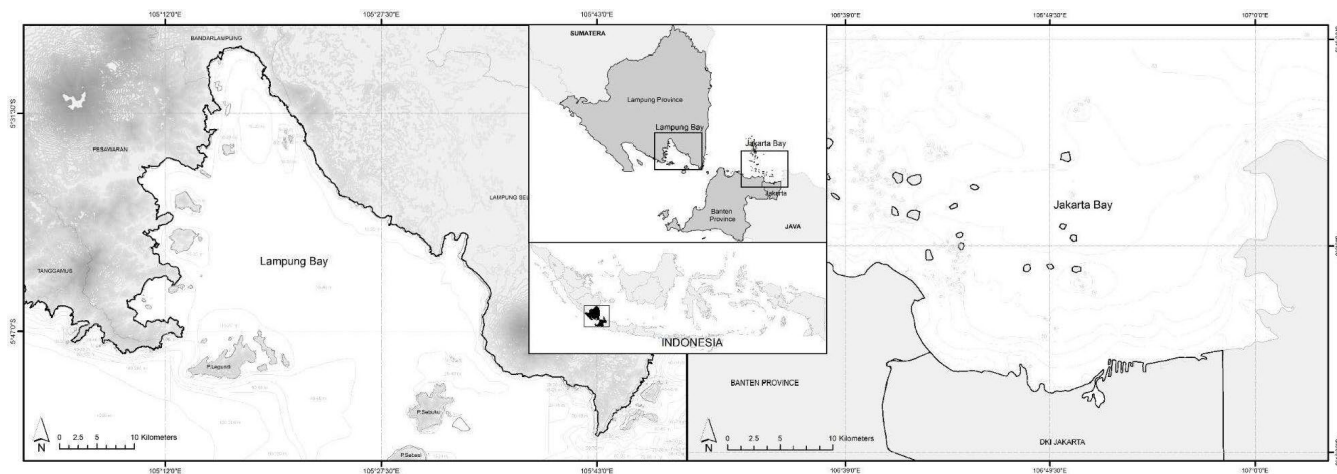
A. STUDY SITES AND DATA

This study took place in two locations, namely, Lampung Bay and Jakarta Bay. Lampung Bay is located in Lampung Province and adjacent to the Sunda Strait, Indonesia. A shallow water area characterizes the bay with an average depth of 20 meters, strongly influenced by anthropogenic activities from the surrounding dense settlements. Tidal currents dominate the water exchange where the water mass from the Indian Ocean enters the bay through the east coast and then directly turns to the west side at the tip of the bay. The current velocity decreases on the west coast of the bay due to coastal morphological conditions, where there are some small bays and small islands along the west coast [18]. As a result, it accumulates nutrient concentrations and generates frequent algae blooms under certain environmental conditions [19].

Jakarta Bay is located in northern Jakarta Province, Indonesia. It is shallow water with an average depth of 12.5 m, affected by the water mass from the Java Sea, where the monsoon strongly influences the movement of the water mass. Similar to Lampung Bay, Jakarta Bay is also strongly influenced by anthropogenic activities.

Lampung Bay and Jakarta Bay received high inputs of nutrients from land activities that generate frequent algae blooms [20]. As a result, the trend of algal blooms in Jakarta Bay has increased since 2000. There are 16 species of algae identified as blooming causative [21], where most of the abundant species found are Skeletonema and Chaetoceros [22]. On the other hand, since 2012, there has been an increase in the frequency of red tides in Lampung Bay caused by the blooming of *Chaetoceros polykrikoides* algae [23]. The data used in this study are algae data obtained from the two bays' water taken from 2017 to 2019. Fig. 1 shows a map of the research sites located in Lampung Bay and Jakarta Bay.

B. KNOWLEDGE BASE

Ontology was used as the knowledge base of the expert system. Apart from being a taxonomic reference of the species and genera understudied, ontology provides axioms as boundaries to give the characteristics of the object. For example, *Alexandrium* is a genus of algae with a flagella length ranging between 16 and 55 μm. Therefore, when the identification process is carried out, if there are algae that do not have flagella or have a length outside this range, the system will refuse to classify the algae into the genus *Alexandrium*. Fig. 2 shows the ontology design process using the Protégé editor.

Another benefit of using an ontology in this expert system is to assist in the "pruning" process. Ontology was used to guide the dialog so that there is no waste of questions given to users. It was done by narrowing down the candidate questions that users ask based on the previous questions. This pruning technique will be explained later in Section II.C.

This study proposed a certainty factor (CF) to determine how confident an expert is in the assertion that an alga under consideration has specific characteristics. CF is used when expert judgment is needed on a statement in the form of object/event features: how sure an object/event has specific features. Two variables must be obtained from the experts, namely, the measure of belief (MB) and the measure of disbelief (MD). The function to calculate the certainty factor, CF, of Hypothesis H given evidence E is defined in Equation (1), where:

$MB(H, E)$ = Measure of belief in Hypothesis H given evidence E (between 0 and 1); and

$MD(H, E)$ = Measure of disbelief to Hypothesis H given evidence E (between 0 and 1).

$$CF(H, E) = MB(H, E) - MD(H, E) \qquad (1)$$

The certainty factor, CF, not only uses values to assume an expert's level of confidence but can also use values from initial facts found by users [24]. For this case, the $CF(H, E)$ is defined in Equation (2), where:

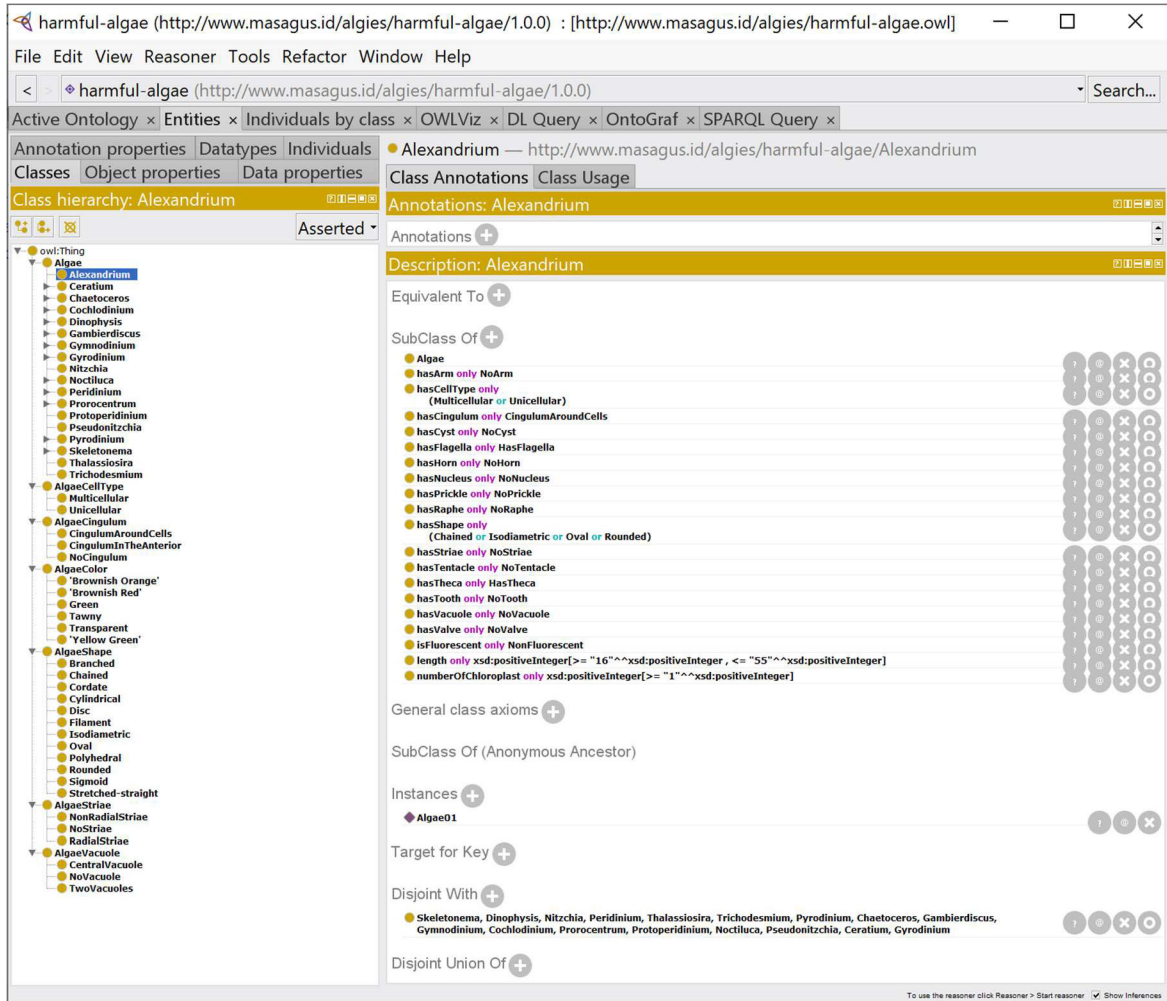$CF(E)$ = the CF value of evidence E determined by the user; and

FIGURE 2. Design of the knowledge base using Protégé.

$CF(Rule) =$ the CF rule value determined by the expert.

$$CF(H, E) = CF(E)xCF(Rule) \qquad (2)$$

Equation (3) combines two or more CFs into one CF that represents these CF values, where:

$CFcomb(CF1, CF2) =$ Combined certainty factor, also called the confidence level (CL);

$CF1 =$ Certainty Factor 1; and

$CF2 =$ Certainty Factor 2.

$$CFcomb(CF1, CF2) = CF1 + CF2x(1 - CF1) \qquad (3)$$

A relational database was used to accommodate the need for certainty factor calculations in the developed expert system, with a structure shown in Fig. 3. The *object_features* table connects the *objects* table with the *features* table, which contains the object relations with its features along with its MB and MD values.

The determination of the values of MB and MD was obtained from expert judgment. The MB and MD values were collected from a number of algae experts and then took the
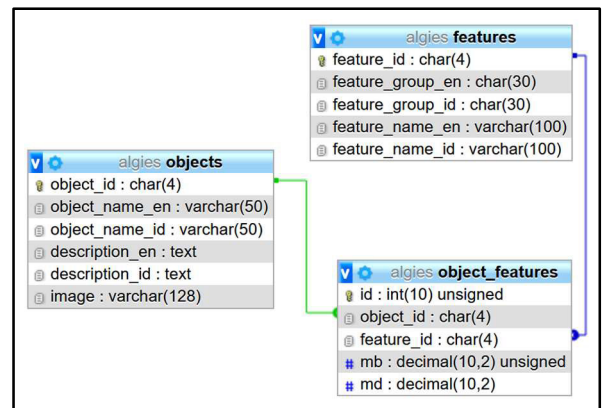

FIGURE 3. Relationship diagram of objects (species/genera) and their features.

average values to be included in the database. Fig. 4 shows the screenshot of the *object_features* table with the processed MB and MD values.

id	object_id	feature_id	mb	md
409	A001	F001	0.44	0.14
410	A001	F002	0.39	0.14
412	A001	F021	0.8	0.02
413	A001	F022	0.45	0.13
		.		
		.		
		.		
539	A020	F060	0.43	0.13
540	A020	F070	0.65	0.21
541	A020	F110	0.75	0.05
542	A020	F140	0.7	0.1
543	A020	F161	0.75	0.03

FIGURE 4. Screenshot of the object_features table content.

C. INFERENCE ENGINE

The application begins by displaying a list of algae images. The user is welcomed to choose an image of the algae that closely resembles the alga to be identified. Next, the system asks the user a question about the characteristics of the alga to be identified. The user only needs to answer 'Yes' or 'No' whether the characteristic is present in the alga in question. The system processes the answer from the user and considers it as input for the question to be asked next. The given answers by the user become provisions for the system to select the candidate objects. The application continues in this loop until one of three conditions is met: (1) the object in question is identified, (2) the object in question cannot be identified, or (3) the user cancels the consultation session. The flowchart of the inference engine is presented in Fig. 5.

It can be seen from the flowchart that three critical processes guide the application in identifying objects. The first is finding the next feature asked in a consultation session with the user (*fetchNextQuestion*). The second is obtaining the selected candidate object(s) based on the questions asked by the system and the answers given by the user (*getObjectCandidates*). The third is calculating the CF value of the selected object given the characteristics that the user determines. The calculation of this CF value was conducted using Equation (1), described in Section II.B.

The *fetchNextQuestion* function takes three parameters: the candidate objects for the alga to be identified, the features asked by the user, and the features selected as the characteristics of the object by the user. The main principle of this function is retrieving the next feature to be asked and obtaining the minimum degree of feature similarity of the candidate objects. It is done so that when the user answers 'Yes' to a feature asked for, the system can eliminate candidate objects that do not have that feature as quickly as possible.

Let us say there is an object set O and a feature set F as follows:

$$O = \{A, B, C\}$$
$$F = \{F1, F2, F3, F4, F5, F6\}$$
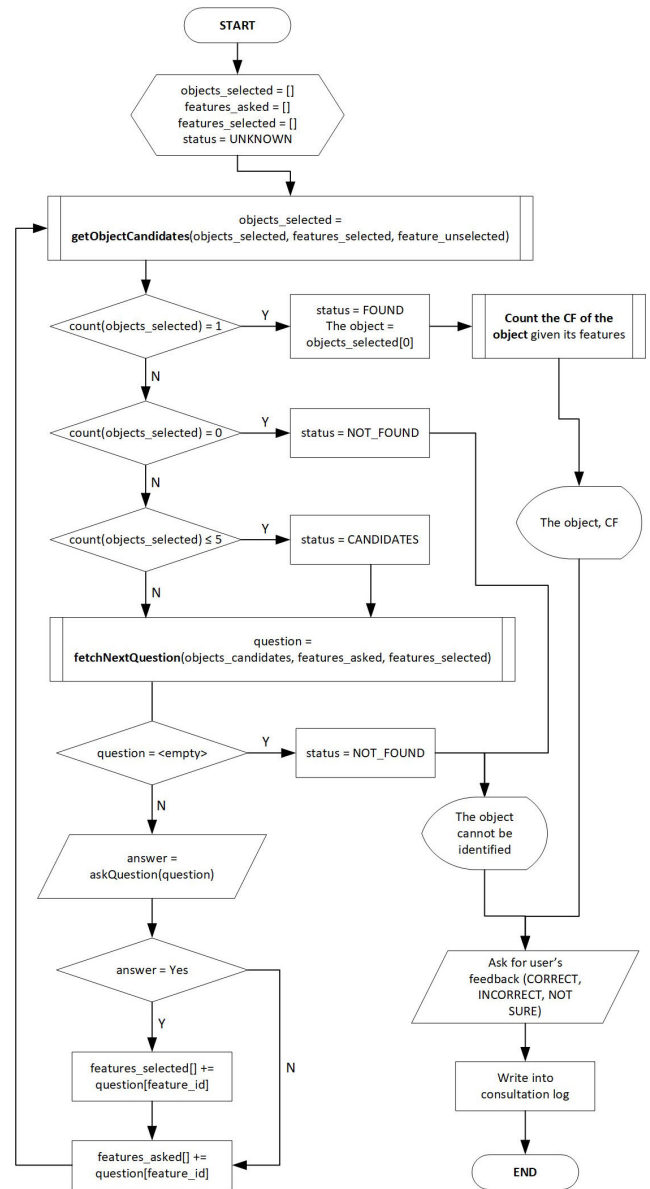
FIGURE 5. Flowchart of the inference engine.

F_N represents the set of features that object N has, for example:

$$F_A = \{F1, F2, F3, F4, F5, F6\}$$
$$F_B = \{F2, F3, F4, F5, F6\}$$
$$F_C = \{F3, F4, F5, F6\}$$

Then, to determine the next feature asked of the user, the features that have the slightest similarity between the three objects were identified. If $\varsigma(F1)$ is the set of feature similarity of $F1$ (the set of objects that have the $F1$ feature) and $\delta(F1)$ is its degree (the number of objects that have this feature), we obtained that the $F1$ feature was chosen for the next question.

$$\varsigma(F1) = \{F_A\} \Rightarrow \delta(F1) = 1$$

Algorithm 1 fetchNextQuestion

Input

    ObjectCandidates: candidate objects for the alga to be identified

    AskedFeatures: features that have been asked of the user

    SelectedFeatures: features that have been selected as the characteristics of the object. Initial value: all features in the
        database

Output

    FeatureCandidate: feature candidate that will be asked of the user for the next question

Description

    This function determines the next feature that will be asked of the user for the next question in a dialog session.

1 **begin**

2 *FeatureGroups* ← enumerate feature groups of *SelectedFeatures*

3 *FeatureCandidate* ← []

4   *Candidates* ← select features of objects in *ObjectCandidates* that are not listed in *AskedFeatures* and do not
        have feature group listed in *FeatureGroups*

5 **if** *Candidates* ≠ [] **then**

6   //get the minimum degree of feature similarity

      if number of elements in *Candidates* = 1 **then**

7   *FeatureCandidate* ← *Candidates*[0]

8   **else**

9   *FeaturesCount* ← []

10   **foreach** *obj* **in** *ObjectCandidates* **do**

11   *Count* ← 0

12   **foreach** *feat* **in** *Candidates* **do**

13   **if** object *obj* has feature *feat* **then** *Count* ← *Count* + 1

14   **end foreach**

15   *FeaturesCount*[*feat*] ← *Count*

16   **end foreach**

17   sort array *FeaturesCount* in ascending order

18   *FeatureCandidate* ← index of first element in *FeaturesCount*

19   **end if**

      //—

20 **else**

21   *FeatureCandidate* ← **null**

22 **end if**

23 **return** *FeatureCandidate*

24 **end**

$$\varsigma(F2) = \{F_A, F_B\} \Rightarrow \delta(F2) = 2$$
$$\varsigma(F3) = \{F_A, F_B, F_C\} \Rightarrow \delta(F3) = 3$$
$$\delta(F4) = \delta(F5) = \delta(F6) = 3$$

The algorithm for the *fetchNextQuestion* function is as follows.

The *getObjectCandidates* function retrieves all objects that have the features selected by the user. It filters the current object candidates based on the new set of selected features and an unselected feature (if any) to generate new object candidates. Objects that do not have all the features listed in the selected features will be excluded from the object candidates. Additionally, when the user answers 'No' for a dominant feature possessed by an object, the object is removed from the list of object candidates. The algorithm of this function is as follows.

D. DIALOG INTERFACE

The expert system was implemented as a web-based application called Algies (Algae Identification Expert System). It can be accessed via a web browser at the URL address http://www.masagus.id/algies/. First entering the application, the user will be shown a welcome screen that contains how many species/genera were included in the database. Then, there is a button to start the consultation and to select the language to be used.

During the consultation session, users were presented with questions generated by the system according to the *fetchNextQuestion* algorithm described in Section II.C. When the user answers 'Yes' that the character was present in the observed alga or 'No' if not, the system selects or excludes object candidates according to the *getObjectCandidates* algorithm. The consultation continues until the alga is found in the

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Algorithm 2 getObjectCandidates

Input
      SelectedObjects: current selected objects
      SelectedFeatures: selected features
      UnselectedFeature: an unselected feature
Output
      Candidates: object candidates
Description
      This function filters objects that have all the features listed in *SelectedFeatures* and do not have a dominant
      UnselectedFeature from current *SelectedObjects*.

1 **begin**
2 *Candidates* ← []
3 *Matrix* ← []
4 **if** *SelectedObjects* = [] **then** *SelectedObjects* ← All objects in the *objects* table
5 **if** SelectedFeatures ≠ [] **then**
6   **foreach** (*obj* **in** *SelectedObjects*) **do**
7   **foreach** (*feat* **in** *SelectedFeatures*) **do**
8   Check whether object *obj* has feature *feat*
9   **if** *obj* has feature *feat* **then**
10   *Matrix*[*obj*][*feat*] ← 1;
11   **else**
12   *Matrix*[*obj*][*feat*] ← 0;
13   **end if**
14   **end foreach**
15   **end foreach**
16   **foreach** (*obj* **in** *SelectedObjects*) **do**
17   **if** sum of *Matrix*[*obj*][*feat*] = number of *feat* **then**
18   push *obj* into *Candidates*
19   **end if**
20   **end foreach**
21 **else**
22   *Candidates* ← *SelectedObjects*
23 **end if**
24 **if** *UnselectedFeature* ≠ <empty> **and** *UnselectedFeature* **not in** *SelectedFeatures* **then**
25   **foreach** (*cand* **in** *Candidates*) **do**
26   **if** *cand* has feature *UnselectedFeature* **and** *UnselectedFeature* is a dominant feature **then**
27   remove *cand* from *Candidates*
28   **end if**
29   **end foreach**
30 **end if**
31 **return** *Candidates*
32 **end**

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database or it can no longer be identified. When the alga is identified, the system then calculates the confidence level of this identification process. At any time, the user can cancel the ongoing consultation session. In addition, a facility to evaluate system performance was added by displaying a feedback form at the end of the consultation session. Fig. 6 shows a screenshot when the user was in consultation with Algies: (a) the system asks about the characteristics of the observed alga, and (b) the system provides identification results based on the characteristics given.

E. EXPERIMENTAL DESIGN

Once the expert system had been developed, it was then tested to see its performance, i.e., how accurately the expert system provided the correct answer from the characteristics described by users. 60 samples of algae that were distributed evenly among three experts were selected. Algies then tried to identify them one by one. Finally, algae experts verified the identification results. Algae identification accuracy is calculated as the ratio of correct answers (correctly identified objects) to the number of experiments, as defined in
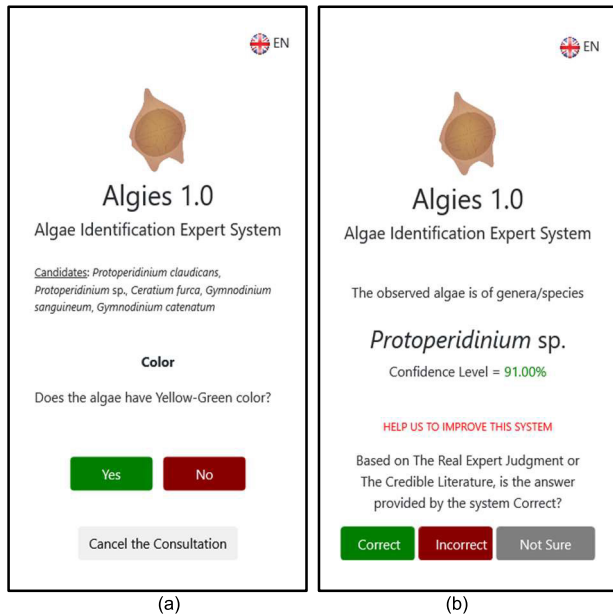
FIGURE 6. Dialog interface of Algies.

Equation (4).

$$accuracy = \frac{\sum correct}{\sum experiment} \tag{4}$$

$$\bar{CL} = \frac{\sum_1^n CL}{n} \tag{5}$$

Equation (5) was used to calculate the overall confidence level. It is the average of all confidence levels for correctly identified objects, where *CL* is the confidence level calculated using Equation (3) and *n* is the number of correctly identified objects.

III. RESULTS
This section describes the results obtained in the research that has been carried out.

A. STUDY SITES AND DATA
Based on the HAB events that occurred in Lampung Bay and Jakarta Bay over the last ten years, the types of algae (species/genera) reported include [21]–[23]: (1) Nitzschia, (2) Pseudonitzschia, (3) *Skeletonema costatum,* (4) Thalassiosira, (5) *Chaetoceros socialis,* (6) *Noctiluca scintillans,* (7) *Protoperidinium claudicans,* (8) *Prorocentrum micans,* (9) *Gymnodinium catenatum,* (10) *Gymnodinium sanguineum,* (11) *Gyrodinium lachryma,* (12) *Pyrodinium bahamense,* (13) *Gambierdiscus toxicus,* (14) Alexandrium, (15) *Ceratium furca,* (16) *Dinophysis caudata,* (17) Protoperidinium, (18) Trichodesmium, (19) *Cochlodinium polykrikoides,* and (19) *Dinophysis.* Therefore, in this study, the focus was on the data collected for these 20 species/genera of algae.

The algal characteristics that were collected from these algae consist of 21 features: (1) shape, (2) length, (3) color,

(4) number of chloroplasts, (5) cell type, (6) fluorescent body, (7) raphe, (8) valve, (9) flagella, (10) prickle, (11) arm, (12) theca, (13) nucleus, (14) cingulum, (15) horn, (16) vacuole, (17) striae, (18) tooth, (19) tentacle, (20) cyst, and (21) setae. These characteristics were then broken down to values that the algae may possess under study. Determination of characteristics also considers the dominant features possessed by an object to make it easier to distinguish it from other objects. The results are shown in Table 1.

TABLE 1. The breakdown of algae characteristics.

No	Characteristic/Value
1	Shape
	(a) Stretched straight (b) Oval (c) Cylindrical (d) Disc
	(e) Rounded (f) Cordate (g) Rounded oval
	(h) Polyhedral (i) Isodiametric (j) Filament
	(k) Branched (l) Vase (m) Chained like a train
2	Length
	(a) $\leq 15\,\mu\text{m}$ (b) $\leq 55\,\mu\text{m}$ (c) $\leq 80\,\mu\text{m}$ (d) $\leq 95\,\mu\text{m}$
	(e) $\leq 120\,\mu\text{m}$ (f) $\leq 230\,\mu\text{m}$ (g) $> 230\,\mu\text{m}$
3	Color
	(a) No Color (Transparent) (b) Tawny
	(c) Green (d) Brownish Red
	(e) Brownish Orange (f) Yellowish Green
4	Number of Chloroplasts
	(a) 1
	(b) 2 or 3
	(c) > 3
5	Cell type
	(a) Unicellular
	(b) Multicellular
6	has Fluorescent body
7	has Raphe
8	has Valve
9	has Flagella
10	has Prickle
11	has Arm
12	Theca
	(a) Theca with cellulose walls (plates)
	(b) No Theca or without cellulose walls (plates)
13	has Nucleus
14	Cingulum
	(a) Cingulum in the Anterior
	(b) Cingulum around cells
15	has Horn
16	Vacuole
	(a) One vacuole
	(b) Two vacuole
17	Striae
	(a) Radial
	(b) Non Radial
18	has Tooth
19	has Tentacle
20	has Cyst
21	has Setae

TABLE 2. The completed expert assessment form.

No	Char	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	1(a)	4.375	4.375													4.5			7		
2	1(b)	3.875	8			3.375		4.75		3.875	4.875				3.875			3.25		5.438	6.375
3	1(c)			5.5		4.475															
4	1(d)				5.375																
5	1(e)						5.25									5		4.875			
6	1(f)								7.625			8						8			
7	1(g)									5.75	4	4.25	5.125	4.75			5			4.875	4.875
8	1(h)									4.875	5.75		7.25					3.875			
9	1(i)													5.5				3.875			
10	1(j)																		7.5		
11	1(k)															8			4		
12	1(l)																8				8
13	1(m)		8	8											6.5						
14	2(a)	8		5	5	5			4.5												
15	2(b)	4.5		4.875	5	7	6	5	4.25	4.5	4.75	4.75	4.25		3.75		3.375	4.75		4.25	4.5
16	2(c)	4.5		5	5.25				5	4.75							4.25	4.25		4	4
17	2(d)			8	4.75												4.25	4		4.125	4
18	2(e)				4									5.5			4	3.75		3.875	4
19	2(f)				4		5.5									5			4		
20	2(g)						6.313	4.875													
21	3(a)	4					4.25				3					8					
22	3(b)	4.375	4.375	4.25		3.875		4.125	5.125		5	4.875		4.25		4.5				5.125	
23	3(c)						9	3.25													
24	3(d)																	8			5.75
25	3(e)													5							
26	3(f)						5	3.75											5.125		
27	4(a)					4						3.875	3.625	4.125	3.75						4.25
28	4(b)	4.375	5.25	4.125					4.25				3.625		3.375						
29	4(c)				3.75						3.625		3.625		3.375	4.25				4.25	
30	5(a)	6	3.875				5.75		5.25	4.25		5.75			3.875	5.75			3.25		6.5
31	5(b)	2.625	5.375	7.75	5.375	4.25				5.125			5.125		5.25				7	6.625	
32	6						4.3125						5.875						5		
33	7	6.125	4																		
34	8	3		4	4.125				4.125												
35	9						9	6.875				5.25		7.375	4.5					7.25	7.5
36	10			3.875	3.375	4.875										5.875		5.375			
37	11																6.75	4.875			
38	12(a)						7.625	6.625					7.625	6.75	6.25	6.875	5.875	7		7.5	7
39	12(b)					8															
40	13		4.125				7.375				3.875									8	
41	14(a)																7.875				
42	14(b)						7.875			7.625	7.875	6.375		7.375	6			8		8	7.5
43	15						8.75										8.875	8.875			
44	16(a)		5.125				5.75														
45	16(b)							6.75													
46	17(a)				6.875									5.75							
47	17(b)	7.375																			
48	18					4.25															
49	19					8.4375															
50	20								8.375					7.75							
51	21					9															

TABLE 3. The criterion range of values for the level of dominance of the feature possessed by a species/genus.

Range	Description
2 — 4	The feature is not dominant (many found in other species/genera)
4 — 6	The feature is quite dominant
6 — 8	The feature is dominant
8 — 10	The feature is very dominant (the main characteristic of the species/genera)

B. KNOWLEDGE BASE

The collected algal data and their characteristics were then compiled into a table of species/genera ↔ feature relationships. There were 51 features possessed by the 20 algae. The table was then given to five algae experts for assessment and validation. The experts have at least ten years of experience in algal identification and analysis. The assessment results are shown in Table 2.

The Char column contains the feature numbers depicted in Table 1. Columns 1 to 20 represent species/genera codes listed in Section III.A. A number in the cell represents a dominance level of the feature possessed by the species/genera. For example, in the first row, Columns 1, 2, 15, and 18 contain the numbers 4.375, 4.375, 4.5, and 7, respectively. This means that the straight Stretched shape (feature no. 1(a)) was owned by the species/genera Nitzschia, Pseudonitzschia, *Ceratium furca,* and Trichodesmium with dominance levels of characteristics, as mentioned above. This value was the average given by the experts according to their beliefs about the feature dominance level possessed by a species/genus. This value was given based on the criterion range of values, as listed in Table 3.

C. EXPERIMENT

Tests were conducted to determine the system's performance in identifying algae types based on their characteristics. First, three algae experts were trained to use and evaluate Algies. One evaluator was from the Ministry of Marine Affairs and Fisheries, and the other two were university academics. Two evaluators held doctorate degrees, and one had a master's degree in related algal science. Each evaluator was then provided with 20 samples of algae to be identified using Algies. The results of algae identification were then compared with the results of evaluator identification, i.e., correct or incorrect. The results of testing the Algies system by the three evaluators are presented in Table 4. The accuracy was calculated using Equation (4). We also calculated the average value of confidence level and accuracy to see the overall system performance. Additionally, the incorrect species/genus names suggested by the system in the last column were captured for analysis purposes.

IV. DISCUSSION

An expert system simulates the judgment of humans by using the encoded knowledge. In general, the quality of a judgment relies on the techniques used to represent knowledge and perform reasoning. For example, correctly identifying HAB-caused species or genera of algae requires precise knowledge. Combining the automated expert system and the quality of encoded knowledge could theoretically overpower the contemporary methods of algal identification in providing rapid results for decision-making. Unfortunately, the lack of automatic identification tools has restricted researchers and laboratory technicians from delivering fast results of HAB causative species.

In this study, a rapid identification system is proposed based on an expert system with certainty factors. First, the morphological characteristics of targeted algae were formalized as a knowledge base (KB). After that, an inference engine was developed to drive a dialog interface between users and the KB. The interface facilitates a structured exploration of the KB through a series of questioning and answering. As a result, the species or genera of a specimen will be identified.

51 algae characteristics were incorporated as features into the expert system. The system was tested on 20 types of algae, where 73.33% accuracy was obtained. From the correctly identified species/genera, the evaluators had high confidence in the results; the confidence levels were between 52.67% and 100%, with an average of 83.51%. The confidence levels were lower from the incorrectly identified species/genera, between 50% to 96.2% and 62.28% on average. This finding indicated that the developed expert system has worked as expected, where the certainty factor has a linear impact on the results. When experts are confident with their judgments, they have a high chance of producing a correct result.

In Table 4, the genus Nitzschia was the object most easily identified by Algies, with the highest confidence level (100%) in each test carried out by the evaluators. This result indicates that the description of the genus Nitzschia was clear and significantly different from the other objects. The other objects consistently identified by the system were *Noctiluca scintillans*, Trichodesmium, *Pyrodinium bahamense*, *Prorocentrum micans* and *Dinophysis caudata*. The system identification results for these species/genera were in line with the identification results of all evaluators with a confidence level above 79.75%.

Algies had consistently misidentified *Gymnodinium sanguineum*. The species was incorrectly identified as *Gymnodinium catenatum*. The result underlines a critical finding that the description of *Gymnodinium sanguineum* has to be improved to differentiate it from *Gymnodinium catenatum* and vice versa. The result also outlines the strength of KBS in feeding its "logical thinking" and "conclusion" for further improvement, as discussed at the beginning of this paper.

One thing that should be noted for further inspection is the identification result of *Gyrodinium lachryma*. There was an

TABLE 4. Application testing results by evaluators.

No	Species/Genus	Expert #1		Expert #2		Expert #3		CL Avg(%)	Incorrect System Identification
		Correct?	CL(%)	Correct?	CL(%)	Correct?	CL(%)		
1	Nitzschia	1	100	1	100	1	100	100	
2	Pseudonitzschia	1	85.5	1	100	1	85.5	90.33	
3	*Skeletonema costatum*	1	72.67	1	66.67	1	100	79.78	
4	Thalassiosira	0	55	1	56	0	55	-	*Gambierdiscus toxicus*
5	*Chaetoceros socialis*	1	65.67	0	72.67	0	72.67	-	*Skeletonema costatum*
6	*Noctiluca scintillans*	1	94	1	94	1	94	94.00	
7	*Protoperidinium claudicans*	1	48	1	55	0	96	-	*Ceratium furca*
8	*Prorocentrum micans*	1	83	1	83	1	83	83.00	
9	*Gymnodinium catenatum*	1	51	1	51	0	48	-	*Protoperidinium claudicans*
10	*Gymnodinium sanguineum*	0	51	0	51	0	51	-	*Gymnodinium catenatum*
11	*Gyrodinium lachryma*	1	94.75	1	94.75	0	100	-	*Gymnodinium catenatum*
12	*Pyrodinium bahamense*	1	88.67	1	88.67	1	88.67	88.67	
13	*Gambierdiscus toxicus*	0	51	1	55	0	51	-	Alexandrium
14	Alexandrium	1	47	1	60	1	51	52.67	
15	*Ceratium furca*	1	45	0	55	0	55	-	*Protoperidinium claudicans*
16	*Dinophysis caudata*	1	79.75	1	79.75	1	79.75	79.75	
17	Protoperidinium	0	55	1	91	0	55	-	*Protoperidinium claudicans*
18	Trichodesmium	1	90.67	1	90.67	1	90.67	90.67	
19	*Cochlodinium polykrikoides*	1	56.67	1	70.67	1	70.67	66.00	
20	*Dinophysis acuminata*	1	93.5	1	93.5	1	94.5	93.83	
	Num of Correct	16		17		11			
	Accuracy	80%		85%		55%		Avg of Accuracy = (80 + 85 + 55)/3 = 73.33%	

inconsistency in the species identification process. Two of the three evaluators showed correct results with a high confidence level (94.75%). However, the other evaluator showed that the result was incorrect with a high confidence level, i.e., 96.5%. This finding indicates that there might be inconsistencies in the weighting of the characteristic dominance level of this species.

Furthermore, the disagreement between evaluators was compared by computing how many evaluators disagreed on a result from the developed expert system. It was found that one evaluator disagreed on 33.33% of the cases, two evaluators disagreed on 55.56% of the cases, and three evaluators disagreed on 11.11% of the cases. As depicted by this result, more than half of disagreement cases (66.67%) were performed by two or more evaluators. This indicated that the judgment of the majority of experts had a high impact on the produced results.

V. CONCLUSION
A novel expert system for identifying algae was proposed in this study. The proposed method used algae morphology knowledge in the form of ontology as the system's guide. Knowledge of 51 algae characteristics was acquired from five algae experts on 20 HAB causative species/genera. Furthermore, certainty factors were used to indicate the level of confidence. The experimental results showed that the

system's accuracy and confidence level of correctly identified algae yielded 73.33% and 83.51%, respectively.

There is room for improvement to increase the system's accuracy, such as attributing different weights for each characteristic or adjusting certainty factors. For example, more weights could be given to the more essential determinants (based on experts' knowledge) of an algae type. Furthermore, the certainty factors could be tuned automatically using machine learning techniques. Additionally, a hybrid approach combining the system with computer vision is worth trying in the future.

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