VISTA: A teaching aid to enhance contextual teaching

Article *in* Computer Applications in Engineering Education · October 2021

DOI: 10.1002/cae.22407

Received: 3 October 2020 | Revised: 22 February 2021 | Accepted: 27 February 2021

DOI: 10.1002/cae.22407

RESEARCH ARTICLE

WILEY

VISTA: A teaching aid to enhance contextual teaching

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Abstract

In this study, an innovative tool for enabling contextual teaching based on visual inputs, named Visual Stimuli-based Teaching Aid (VISTA), was developed. This system establishes the meaning and significance of concepts that are taught in the classroom within different environmental contexts. The idea of contextual teaching has been deliberated for more than a decade now. Nevertheless, using this in a classroom with limited time and resources has several challenges. VISTA leverages the ubiquitous mobile devices to boost conventional teaching methods with contextual teaching–learning. With VISTA, contextual teaching does not require any specialized device, expensive sensors, or simulated environment. To assess the applicability of VISTA in computer science education, we gathered the responses and experiences from 42 computer science teachers teaching in various universities of India. The responses garnered indicate that contextualization through VISTA is relevant as well as interesting. In total, 86.31% of the teachers found the contextual information provided by VISTA to be significantly related to both the captured images and the concepts presented in the class. These results encourage the use of VISTA as a pedagogical tool for contextual teaching.

KEYWORDS

computer science education, contextual teaching and learning, mobile learning

1 | INTRODUCTION

According to situated learning theory, learning is incomplete without context, culture, and activities that engage students. It states that learning occurs within a particular context. The basic idea behind the theory is making learning meaningful with everyday practices and real-life situations [16]. For this, the theory advocates the use of contexts in which a concept is applied while teaching. Context is the environment or situation comprising real-world entities in which the concepts we learn in classroom are applied [22]. Several studies claim that context is crucial to understand the significance and meaning of the concepts [10,30], to motivate learners [6], and to help derive a coherent structural meaning of the learning material [9]. Educators believe that context is an integral part of teaching the theories and concepts of any subject, including computer science [5]. Contextual teaching also improves understanding of computer science concepts, as it helps in the directive construction of meaning by eliminating ambiguities [23]. These studies make it clear that context has an irreplaceable role in the teaching–learning process.

Situational learning, hence, revolves around creating a situational context for learning that resembles real-life applications [27]. Contextual teaching is a pedagogical approach that helps in the creation of such contexts and bringing alive their role in applying the concepts taught.

Contextual teaching tools are being developed and used to bring in proactive changes to the teaching–learning process [6]. Researchers have used contextual teaching to help students learn a particular subject or a set of concepts in computer science education [1,2]. The benefits of contextual teaching are widely accepted for computer science as well as other subjects [11].

In this paper, we introduce Visual Stimuli-based Teaching Aid (VISTA)—a contextualizer with an aim to incorporate the context while teaching any computer science course. Here, we perceive "contextual teaching" as teaching fundamental theories, abstract concepts, and complicated principles of computer science with real-life applications [4,5].

VISTA makes use of visual stimuli that the teacher takes from the dynamic environment. The aim is to find out applications of a specific concept in the stimuli. Using Natural Language Processing techniques and an e-book, the system extracts important concepts. With the help of Wikipedia, the visual cues and various filters, and a ranking algorithm, the system finds out class concepts with image objects/themes. Finally, it recommends the relevant and interesting context of concepts to teachers. This enables the teachers as well as students to find extensional knowledge that they would not have otherwise discovered. The salient features of using VISTA as a pedagogical tool for teaching are given next.

According to Arnold et al., teaching is believed to be efficient only if the learner can connect the classroom studies to real-life contexts [1]. The system we propose provides a real-world context, hence benefiting the learning process. The argument that context is an inextricable aspect of learning motivates us to think beyond content [6]. Contrary to this, challenges like lack of training and excessive content obligate a teacher to stick to textbooks [20]. VISTA attempts to remove the barriers and allow every teacher to adapt contextual teaching without going through any manpower training. In addition to this, some of the approaches proposed in the literature rely on the deployment of immersive sensors and specialized hardware to capture the context and interactions therein. However, the system proposed facilitates contextual teaching without additional expenses or a simulated environment. The users only need a mobile phone to improve the teaching–learning process. As addition of context helps the students understand the concepts better [9], VISTA can be used as a pedagogical tool to improve the understanding of different computer science concepts.

The rest of the paper explores the existing methods for adopting context in teaching along with the analytical studies concentrating on the use of context. Then, the introduction to VISTA, a tool for teaching in context, is presented. In the end, the results and analysis of the outcomes are presented.

2 | BACKGROUND

In the past, most novices found computer programming a challenging and even intimidating endeavor. However, in recent times, students have started enjoying learning new programming languages [12]. This remarkable shift in attitude and learning aptitude has been made possible due to programming environments like Alice [25] and Scratch [17] that enable teaching computer programming in context. With such programming environments, students can program in context that closely resembles the real-life application of coding. There is a multitude of such simulated environments serving as context for novice programmers, simulating real-world environments [18,32]. However, there are a number of attempts made to teach some useful concepts of other computer science subjects through contextual teaching. For instance, in the study reported by Reference [3], teaching introductory courses in computer engineering and electrical engineering using context was attempted. The context used in this study is the simulation of an electronic system, a global positioning system (GPS) and a programmable robot. Students are also taught some crucial concepts of computer science and mathematics in two different learning environments—LogicTraffic and QueueTraffic [1].

On the one hand, we have sufficient proof of simulations helping in contextual teaching, thereby making learning interactive, interesting, and effective [24,28]. On the other hand, it is also a fact that designing and developing a realistic dynamic environment for every subject of computer science, ranging from simple to complex, is quite expensive and time-consuming [11]. So, this definitely is not a feasible way to move toward contextual teaching from conventional teaching.

One alternative that several teachers have used is to use context passively rather than teaching using simulated environments. A number of context extractors using some sensors are available to facilitate contextual teaching. Personalized Knowledge Awareness Map for Computer-Supported Ubiquitous Learning (PERKAM) is one such context extractor. It detects the objects surrounding the learner, his/her location, and so on, using RFID ubiquities technology [8]. The system then utilizes this information to give personalized knowledge awareness maps that assist in learning. Using the same technology for sensing, Derntl and Hummel [7] tried to establish a link between context and learning activities of the learner. Context here too is the time, location of the learner, and nearby people.

It is observed that in most of the scenarios of contextual teaching, either it is through simulated environments or using some sensors that sense the environmental context. As far as the studies involving games and puzzles are concerned, they limit concepts to a few topics of computer science [2,31]. However, using contextual teaching as a pedagogical tool is possible only if one can facilitate it in a way that is neither too expensive nor time-consuming and can be used for teaching any computer science course. In this paper, we try to give a novel approach to teaching computer science with context. Rather than taking help from expensive sensors, the system we propose gathers information from a mobile phone camera, making contextual teaching feasible.

3 | VISTA—A PEDAGOGICAL TOOL

There are three important considerations that play a significant role in determining the success of designing a system for contextual teaching [21]. The first consideration is as follows: Which context should be captured? As the use of real-life examples that a student can relate to serves as context [15] in developing VISTA, we take into account the physical context. The second significant consideration is as follows: How can this context be captured? In our system, the teacher captures images from the environment using a mobile phone camera. Although it may be any image captured, it can be expected that the teacher would capture a part of the environment in which the concepts taught may have been applied in some way. However, even if such deliberate thought is not applied, VISTA tries to mine related information from any given picture to discover latent correlations and bring in an element of serendipity. The question "How can the context be visualized?" is the third determining factor. VISTA recommends information sources that depict some interesting aspects such as applications of concepts within an environmental context.

Figure 1 shows the overall architecture of VISTA. As shown in this diagram, VISTA takes as input images of teacher's notes and an image of the physical environment. In the following sections, we will explain its detailed working. For the sake of brevity, in this section, we retain a generic description of VISTA that illustrates its core concepts and mechanisms. To illustrate its working, we have included an example in the appendix.

3.1 | Preprocessing teacher's notes

The system accepts images of the teacher's notes. To convert the notes into a form that can be processed conveniently, the system first converts notes into a textual format using an optical character recognition (OCR) system. The system stores the set of words thus recognized in a set *T*. Figure A1 in the appendix is the image of teacher's notes given as input to the OCR. The corresponding text extracted is also available in the appendix. As special symbols do not add a considerable value to information we aim to extract, VISTA eliminates all special symbols by replacing anything other than English alphabets with null characters.

The class notes of computer science are usually a blend of general terms and subject-specific terms.

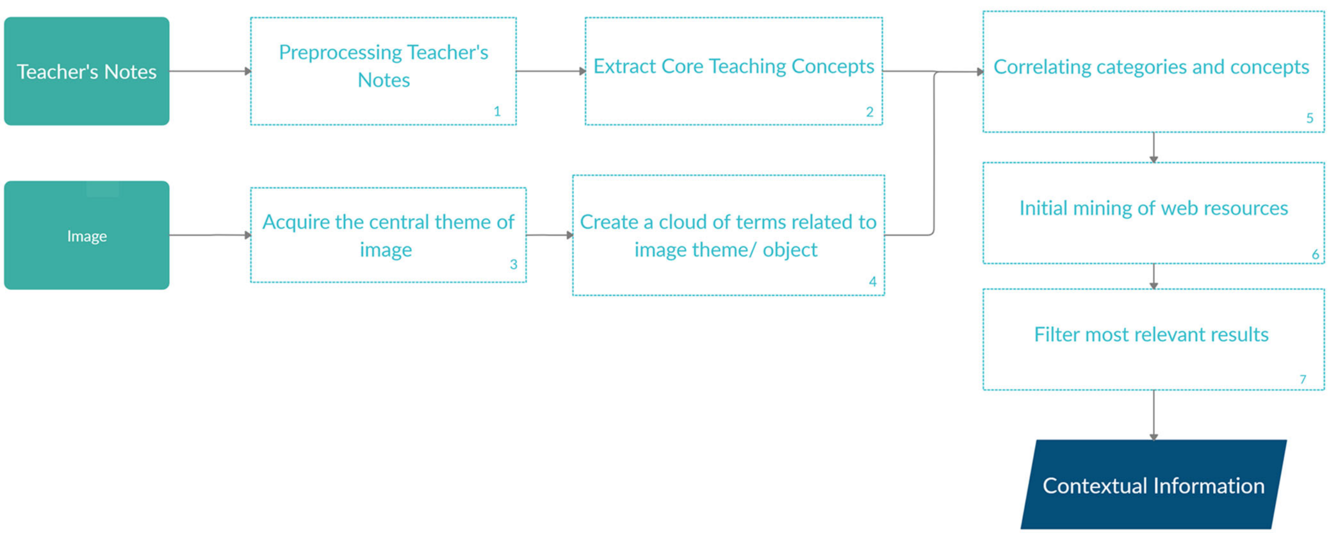


FIGURE 1 Architectural diagram of Visual Stimuli-based Teaching Aid

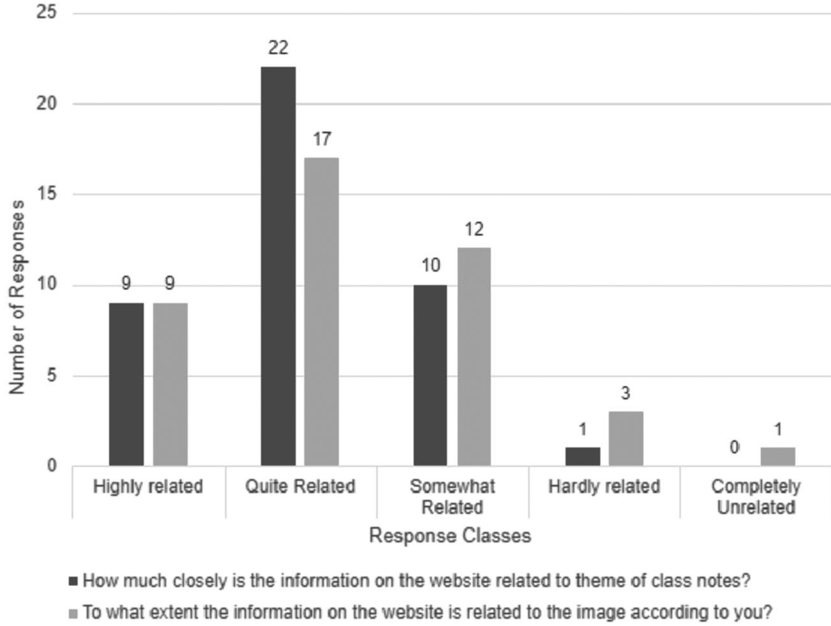


FIGURE 2 Distribution of responses for recommendations on an artificial intelligence data set

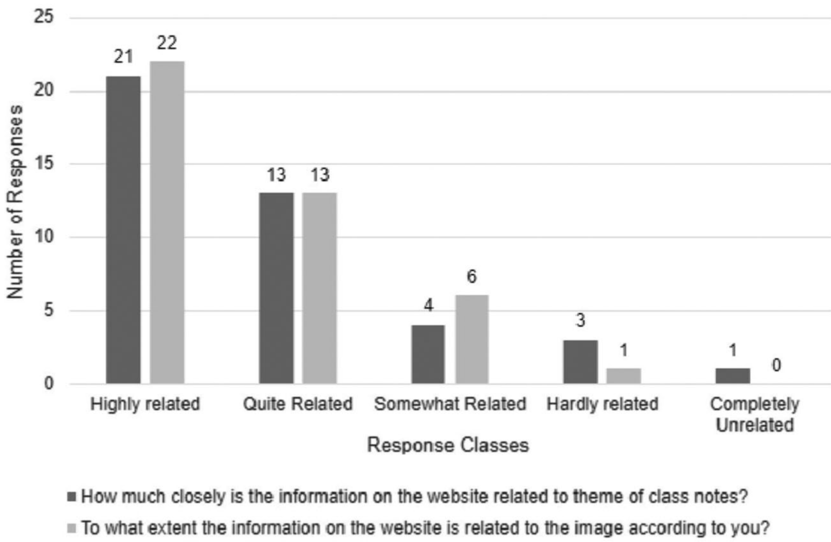


FIGURE 3 Distribution of responses for recommendations on software engineering-I data set

To include the subject-specific words, VISTA refers to the Oxford dictionary of computer science. Every word w from T is searched for in the dictionary and those matching exactly with any term in the dictionary are removed from T and added to a set T'. Remaining words in T are checked for spelling mistakes using a spell checker [26]. If w is present in the English dictionary, it is added to T' as it is. Else, after converting the word into closest match with a dictionary word, the system adds the word to T'. After corrections, the system employs a POS tagger to annotate each word present in T' as a noun, verb, and adjective. Words extracted from a part of notes along with the tags are included in appendix as example.

3.2 | Extracting core teaching concepts

For a set of subjects in computer science, the system maintains an index of corresponding e-books. What we get in T' is a set of fragmented words. However, phrases carry a lot of information in class notes. So, there is a need to cull out phrases, and for this, VISTA uses the index of an e-book. With the notes and index, the system extracts the fundamental concepts embedded within the notes by first selecting the informative words. The system selects and stores all nouns present in T' in a set T_N, as it is widely accepted that nouns convey most of the crucial information present in a text [14]. Apart from nouns, the system also stores all words marked as foreign words in

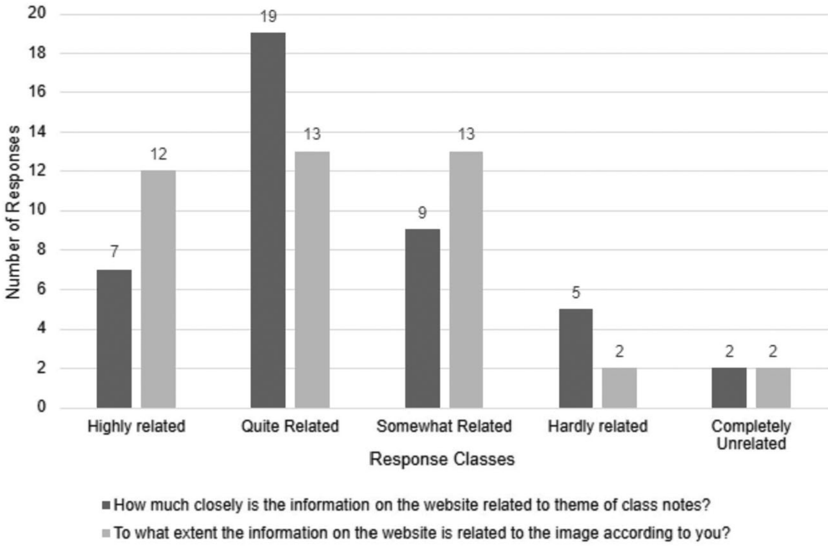


FIGURE 4 Distribution of responses for recommendations on machine learning data set

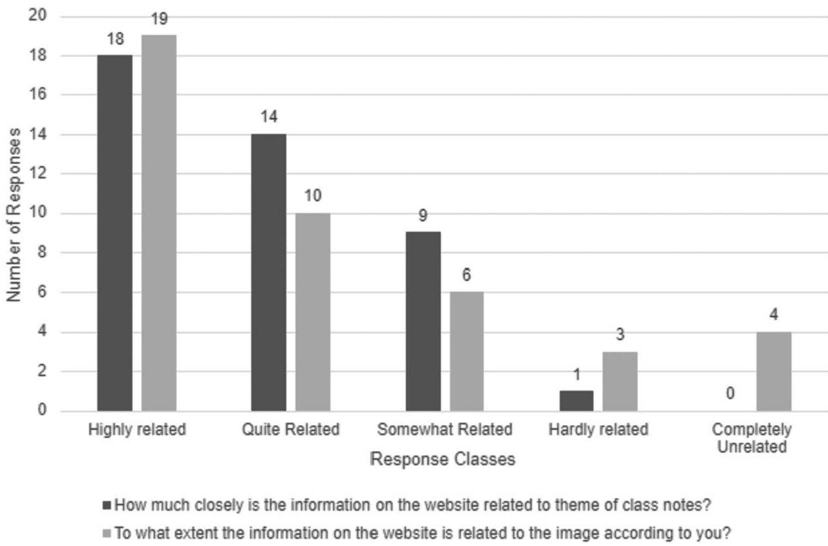
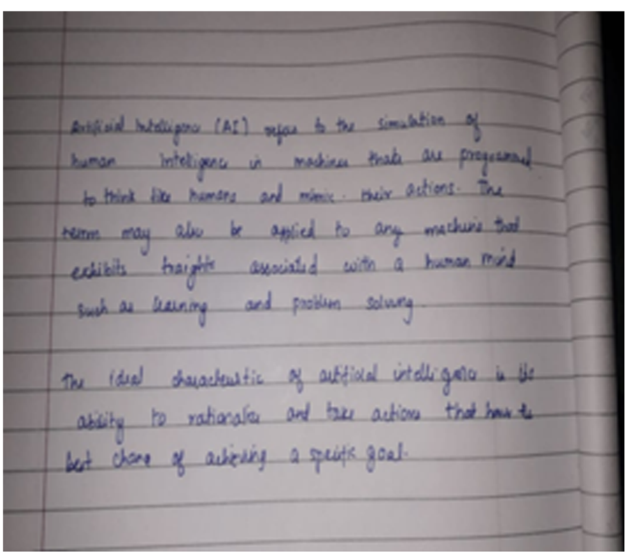


FIGURE 5 Distribution of responses for recommendations on software engineering-II data set


Artificial Intelligence (AI) refers to the simulation of human intelligence in machines that are programmed to think like humans and mimic their actions. The term may also be applied to any machine that exhibits traits associated with a human mind such as learning and problem solving.

The ideal characteristic of artificial intelligence is the ability to rationalize and take actions that have the best chance of achieving a specific goal.

FIG. A1 Portion of teacher's notes

FIG. A2 Image

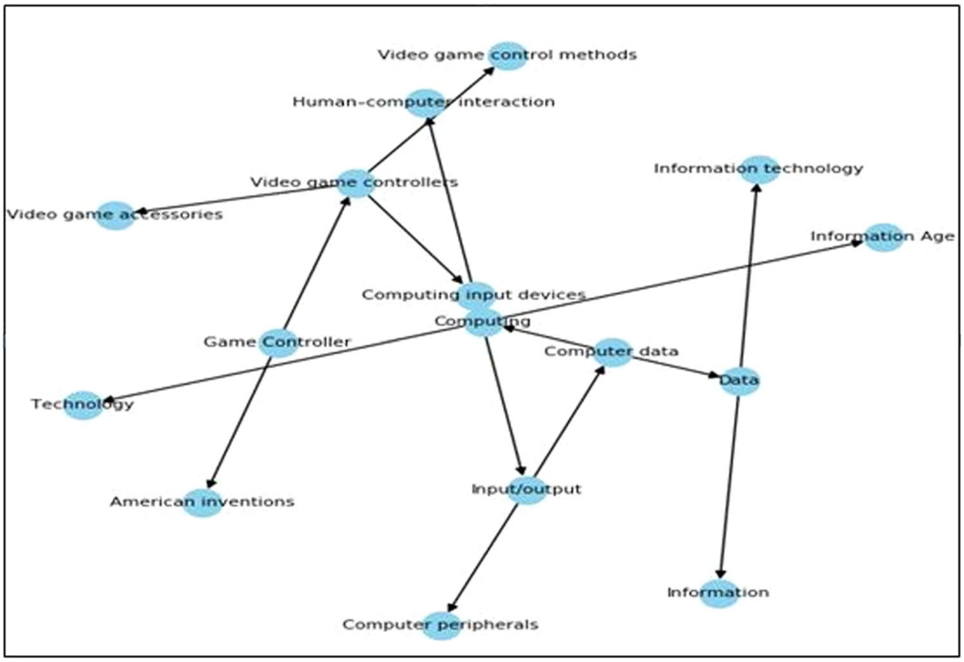


FIG. A3 A sample graph depicting categories related to "game controller"

the previous step in T_N, as these words carry subject-related information:

$$T_N = \{\mathrm{w} \mid \mathrm{w} \in \mathrm{T}' \wedge \mathrm{w} \in (\text{noun} \cup \text{foreign word})\}$$

VISTA now searches the entries in the index of the e-book for every word w in T_N to get the candidate teaching concepts from informative words. For this, it stores the set of index terms of a particular e-book. It chooses all the single or multiword phrases present in the index that contain the words in T_N. All such index entries represent the candidate fundamental teaching concepts stored in C. Let I be the index terms, then C would be represented as follows:

$$C = \{w' \mid w' \in (i \in I)\},$$

C gives us candidate teaching concepts. However, if there are generic terms, it will have a large number of index terms. There is a need to remove such anecdotal mentions. For this, VISTA creates clusters of all index entries in C on the basis of page numbers. A dense cluster having nearby pages indicates a core theme of the class, whereas a sparse cluster usually indicates anecdotal mention. To pick up the core concept, VISTA chooses the densest among all the clusters. Let this cluster be denoted as D. In case there are two or more clusters with exactly equal candidate concepts, all of them are taken as D to avoid loss of information. The topics/index phrases appearing in the densest cluster represent core teaching concepts (TC):

$$TC = \{c \mid c \in C \wedge c \in D\}.$$

3.3 | Acquiring the central theme of image

Almost every course of computer science is applicable in a wide variety of real-life objects and scenarios in many different ways. However, to keep the process of contextualization directed and interesting, VISTA takes as input a particular scene/object/environment. As teachers have a better understanding of what would be interesting for the students [22], the system allows the teacher to select a particular scenario or object from the real world. The image uploaded by a teacher may be of a single object, multiple objects, or even an entire scene comprising a real-life situation. The system processes the image to detect its central theme using Google reverse image search. For example, if Figure A2 is given as an input, it leads to the theme "game controller."

The search engine stores a large number of images along with metadata. With the help of the metadata, every image search results in accurate labels along with other similar images. These labels are the theme of the image uploaded. Let I_T be the image theme or ideas the system extracts from the image. To get theme of image, VISTA gives the image teacher submits as an input to Google image search. From the Search engine result page, it extracts the "possible related search" field appearing on the search engine result page as it contains the label of the image. The label or labels thus obtained are stored in the set I_T.

3.4 | Creating a cloud of terms related to image theme/object

The terms in TC are subject-specific terms and I_T usually describes the image in generic terms. To increase the probability of digging out most meaningful connections from the web resources, VISTA widens the central theme of the image and tries to cull out the technical aspect of the image theme. With the use of I_T, the system creates a cluster of related terms using Wikipedia categories. Wikipedia categories are terms directly related to the title of the Wikipedia page. To create a cloud of terms related to the image, we first extract the base-level categories of Wikipedia. From the uniform resource locators (URLs) of Wikipedia pages corresponding to every idea in I_T, VISTA extracts the category/categories. We call these categories base-level categories. The set of base-level categories represents the terms that are directly connected to the image idea. All such categories are stored in U_{Icat}:

$$U_{Icat} = \{\text{cat}_1,\ \text{cat}_2 \ldots \text{cat}_\text{m}\};\ \text{here, } cat \text{ is a Wikipedia category and } m \geq |\ I_T\ |.$$

After collecting the base-level categories, other related terms are collected. To get all other terms, the system visits the Wikipedia page of the category for every category in UI_{cat} and updates U_{Icat} with the categories present on that page. As the process can end up collecting all the Wikipedia categories in UI_{cat}, there is a need to define a termination condition. For demonstration purposes, we stop the traversal once we have 500 categories in UI_{cat}. A graph, G_{cat}, is created using the Wikipedia categories available in UI_{cat}, such that

$$G_{cat} = \{V,\ E\}.$$

Here, V is a set of Wikipedia categories from UI_{cat} and E is the set of edges. Each directed edge represents that the target vertex is present as a category in the wiki page of the source vertex. If a category appears more than once, the one near to the base-level category is stored. Figure A3 is a sample graph for one category of Wikipedia, which is given in the appendix.

3.5 | Correlating categories and concepts

Searching for web resources using all the categories combined with core teaching concepts in TC is inefficient and may lead to diverse results. VISTA, hence, moves on with category concept pairs that show signs of relatedness through Wikipedia. If a concept from TC is present in G_{cat}, it is assumed that there is some relation between the two. Let TC_R contain the core teaching concepts directly or indirectly related to the categories:

$$TC_R = \{c_r\colon c_r \in TC\ \wedge c_r \in G_{cat}\}.$$

3.6 | Initial mining of web resources

VISTA is now left with concepts from TC_R that are likely to have applications in direction given by the image idea, reducing information overload. The system now mines the web information to come out with meaningful connections. For this, search queries are generated. The system formulates a search for every combination of concept from TC_R, categories in G_{cat}, and subject name:

$$\text{Search query} = <\text{“concept from } TC_R\text{”} + \text{“category from } G_{cat}\text{”} + \text{“}S\text{”} > . \tag{1}$$

With the search queries thus generated, the system conducts preliminary search. It stores the top 10 results obtained from every search query on the search engine result page (SERP) in the list Initial Results (IR).

3.7 | Filtering most relevant results

A combination of basic filtering and a secondary ranking algorithm based on semantic similarity enables VISTA to reach context that best represents the applications of classroom concepts. Basic filtering is applied to select best results from IR. It ensures there are no advertisements, products, and some other promotional websites in the results. The system filters out web pages with no occurrence of at least any two components of search query and applies a filter with a preset list of stop_words such as “amazon,” “flipkart,” and “youtube.”

VISTA now has a list of websites that carry information somehow relevant to the search query. However, there may be results that are either focusing only on the classroom concepts or web pages with information confined only to the image. The system, hence, evaluates semantic closeness of every website in IR with the image idea as well as the core teaching concepts. It uses semantic similarity methods using the Global Vectors for Word Representation (GloVe) algorithm [13]. The overall semantic similarity score represents how much similar the content of a web page is to a given image category in G_{cat} and any core teaching concept in TC_R. It is calculated using the similarity metrics proposed by Reference [13]. A list of websites sorted according to similarity can be seen in the appendix.

3.8 | Recommending the context of concepts

VISTA sorts the list of websites in filtered IR in decreasing order of overall similarity scores. The websites that are most similar to both the concepts the teacher wants to teach in class and categories adding context to the concepts are recommended as context to the teachers.

4 | MATERIALS AND METHODS

VISTA is developed as an Android application that interacts with a Node.js server. On receiving the required inputs, the server spawns Python scripts and formulates appropriate search queries after digging out necessary search keywords. The system uses Google Cloud Vision OCR to convert notes of the teacher from Portable Document Format (PDF) to text format (https://cloud.google.com/vision/). It searches with the image as a search query on Google reverse image search. The software with the use of its huge metadata of images not only detects objects accurately, but also provides the overall theme as "possible related search." To get all the specific concepts related to the image idea, VISTA uses Wikipedia. Wikipedia is a huge repository of information resulting from a continuous collaborative effort [19]. Apart from information about an entity or an event, Wikipedia provides entries on a vast number of named entities and very specialized concepts called categories [29]. The system extracts these categories using beautifulsoup (BS4), a web crawling tool. In the end, we used the Google search engine to mine the websites representing contextual information for recommendations. The Selenium WebDriver was used to gather information from the Web. For filtering and removal of stop words, we use the definition given by the NLTK stop-word corpus.

4.1 | Data sets

We took the list of teachers from different universities and colleges in north India. For demonstration purpose, we took three popular subjects, namely Machine Learning (ML), Artificial Intelligence (AI), and Software Engineering (SE). It was observed that out of the total 110 teachers listed, 50 were associated with at least one of the three subjects. These teachers were requested to share notes on any topics from the three subjects mentioned above. Along with every class notes, they were asked to upload an image of either their surroundings or any specific object. With this, a total of 42 teachers responded and we collected 168 data sets consisting of notes and images.

4.2 | Survey response

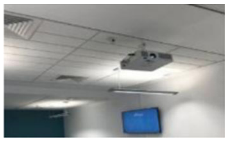
To assess the usefulness of VISTA in teaching, we conducted a feedback evaluation of the system with teachers who had contributed toward providing the data set. The survey questionnaire comprised four psychometric questions listed in Table 1. Question 1–3 had graded responses on a 5-point Likert scale. Question 1 seeks to assess the relevance of the top-recommended website to the class notes, whereas Question 2 assesses its relevance to the associated image. Question 3 gauges how interesting the recommendation is in terms of generating contextual information. Question 4 assesses the practical use of VISTA on a 3-point Likert scale. In addition to these, Question 5 was included to qualitatively analyze the experience of users with VISTA, in their own words.

Every teacher first interacted with VISTA to judge the overall experience with the app. Rather than giving different recommendations to the participants, we input the same set of randomly selected class notes and an image for each subject to VISTA, as shown in Table 2. The

TABLE 1 VISTA feedback questionnaire—questions and their response options

Q. No	Question	Responses
Question 1	*How closely is the information on the website related to the theme taught in the class?*	1: Completely unrelated; 2: Hardly related; 3: Somewhat related; 4: Quite related; 5: Highly related
Question 2	*To what extent the information on the website is related to the image according to you?*	1: Completely unrelated; 2: Hardly related; 3: Somewhat related; 4: Quite related; 5: Highly related
Question 3	*How interesting do you think the students would find the contextualization?*	1: Completely uninteresting; 2: Hardly interesting; 3: Somewhat interesting; 4: Quite interesting; 5: Extremely interesting.
Question 4	*How likely are you to use VISTA in teaching?*	1: Not at all; 2: May use it sometimes; 3: Will definitely use it
Question 5	*Describe your experiences of using VISTA in a few words*	Capture teachers' own experiences with the VISTA.

TABLE 2 The topic of notes, images, and topmost recommendations by VISTA

Data set	Subject (Theme of class)	Image used	Title of topmost recommendation (URL)
AI	Artificial Intelligence (Introduction to neural networks)		Create your own board game with powerful AI from scratch (https://towardsdatascience.com/create-your-own-board-game-with-powerful-ai-from-scratch-part-1-5dcb028002b8)
SE-I	Software engineering (Prototype software development model)		Improving the process of making rapid prototyping models from medical ultrasound images (https://www.researchgate.net/publication/241500139_Improving_the_process_of_making_rapid_prototyping_models_from_medical_ultrasound_images
ML	Machine learning (Ensemble learning)		A stem-based teaching platform (https://www.researchgate.net/publication/337720543_FLUURMAT_-_A_STEM_BASED_TEACHING_PLATFORM?sa=X%26ved=2ahUKEwiv_Pz_3fbmAhXULqYKHfNdDFwQFjAKegQIBBAB)
SE-II	Software engineering (Introduction to software development lifecycle models)		The fountain model and its impact on project schedule (https://www.researchgate.net/publication/234800733_The_fountain_model_and_its_impact_on_project_schedule)

Abbreviations: AI, artificial intelligence; ML, machine learning; SE, software engineering.

corresponding recommendations that were generated by VISTA were made available to all respondents. We maintained this uniformity to initially test VISTA with questions 1 and 2, without bias. One subject, SE, is taken twice purposely just to give an idea of how recommendations are dependent not only on subjects but on topics as well. However, for responding to the remaining questions, the teachers were encouraged to use VISTA freely with their own notes and images. All the teachers were requested to carefully go through each set of inputs and then browse the recommended websites for evaluation.

5 | RESULTS

We analyze the relevance of the recommended links with the class notes as well as with the image input to the system. In addition, we gauge the usefulness of VISTA by way of enhancing contextual teaching–learning and its applicability. We qualitatively assess users' satisfaction with regard to their experience with the system.

5.1 | Assessment on the relevance of recommendations

Table 3 depicts the relatedness of recommended links with the associated class notes, as perceived by the teachers. We record the median and mode of the responses as measures of central tendency, as mean does not have any real meaning for the ordinal Likert scale. For the AI and ML data sets, the median and mode are both 4. As many as 31 respondents (73.8%) for AI and 26 respondents (61.9%) for ML have expressed that the recommendations are quite or highly relevant to the class notes. For SE-I, the mode class and median class are both 5, with 21 respondents (50%) finding the recommendations highly relevant with class notes and a total 34 teachers (80.9%) finding it quite or highly relevant. For SE-II data set, the median class is 4 and mode class 5 with 18 respondents (42%). There is a slight tilt toward class 5, but a majority of 32 respondents (76%)

TABLE 3 Responses for relatedness of recommendations with class notes

	Relatedness classes						
Data set	1	2	3	4	5	Median class	Mode class
AI	0	1	10	22	9	4	4
SE-I	1	3	4	13	21	5	5
ML	2	5	9	19	7	4	4
SE-II	0	1	9	14	18	4	5

Abbreviations: AI, artificial intelligence; ML, machine learning; SE, software engineering.

TABLE 4 Responses for relatedness of recommendations with image

	Relatedness classes						
Data set	**1**	**2**	**3**	**4**	**5**	**Median class**	**Mode class**
AI	1	3	12	17	9	4	4
SE-I	0	1	6	13	22	5	5
ML	2	2	11	14	13	4	4
SE-II	4	3	6	10	19	4	5

Abbreviations: AI, artificial intelligence; ML, machine learning; SE, software engineering.

found the recommendations either quite relevant or highly relevant to class notes.

Table 4 shows the distribution of responses for the relatedness of the recommendations with the image. The mode and median for AI data set are 4, showing that the responses are focused toward the quite related category. A total of 26 respondents (61%) voted for the recommended link to be quite related or highly related with the image. For the ML data set, 27 respondents (64%) found the recommended link to be quite related or highly related to the image. The mode and median for the responses to SE-I data set are both 5, indicating a distinct tilt toward the highly relevant category. For SE-II data set, 19 respondents (45%) responded to the question on relatedness with image by choosing "highly related." Its median is 4, but the mode is 5, indicating a slight left skew. However, a majority of 69% of respondents found the recommended link to be quite or highly related to the image.

Table 5 summarizes the responses for relatedness in percentage, considering both class notes and images. Respondents who found recommendations irrelevant to both are those who chose Options 1(completely irrelevant) or 2 (hardly relevant) for Questions 1 and 2. Those who chose Options 1 or 2 for Question 1 with ticked Options 3 (somewhat related) or 4 (quite related) or 5 (highly related) for Question 2 represent the number of participants who found the recommendation relevant to image but not to class notes. Similarly, a tilt toward class notes is also calculated.

SE-I data set received the highest responses in favor of relatedness with both the inputs. It is worth noting that 90.48% of respondents found the recommendations from VISTA at least somewhat related to both. Only 2.38% responses indicate that the information was only about class notes. Apart from the SE-I data set, 88.1% of the teachers taking the survey felt that the AI data set was also appropriately related with both the elements. ML and SE-II data sets received similar responses, as

TABLE 5 Responses for relatedness with image and class notes

Data set for Subjects	**Percentage of respondents who found recommendation irrelevant**	**Percentage of respondents who found recommendation relevant to notes but not image**	**Percentage of respondents who found recommendation relevant to image but not class notes**	**Percentage of respondents who found recommendation relevant to both class notes and image**
AI	0.00	9.52	2.38	88.10
SE-I	2.38	2.38	4.76	90.48
ML	9.52	0	7.14	83.34
SE-II	2.38	14.28	0	83.34

Abbreviations: AI, artificial intelligence; ML, machine learning; SE, software engineering.

88.34% of the respondents found that the contextual information matched with the class theme and image in the data set. No one felt that the contextual information in the data set was inclined only toward the class notes in ML data set. SE-II data set also received *zero* responses in favor of inclination only toward the image.

5.2 | Evaluation of contextualization and usefulness of VISTA

We analyzed the responses to Question 3 to assess the interest factor of contextualization with VISTA. A majority 61.9% of the teachers found the contextualization outcomes to be quite interesting and 11.9% respondents felt the system was somewhat interesting. However, a predominant majority, 97.6%, of the responses indicate varying levels of interest of the teachers, and only one of them found it completely uninteresting.

5.3 | Qualitative evaluation of users' experiences with VISTA

With only one participant finding it not so useful, all others displayed the willingness to use VISTA as a teaching aid in future. The responses for overall experiences with VISTA indicate enthusiasm among teachers. The most frequent term seen in the description was "educational." Teachers also found the entire idea useful, as we saw another frequently occurring phrase "I found it useful." Apart from this, "interesting," "something different," and "awesome" were also seen as descriptions of the system. However, a few participants felt that the length of the text in the contextual idea was too long.

The results of the survey indicate clearly that the teachers are enthusiastic to use tools like VISTA. With an overall 86.31% respondents finding the contextual information related to both the image as well as class notes, it can be said that VISTA recommends the context of concepts with a good degree of relevance. Apart from relevance, 97.6% of the teachers found the system interesting enough, as the level of contextual information is enhanced.

6 | CONCLUSION

We developed a tool named VISTA to facilitate teachers by harnessing real-world contextual information to add value to any concept that they want to teach in class. To the best of authors' knowledge, this is the first time that an automated system lends teachers the power of teaching with real-life examples by correlating the latent information in a picture with class notes and recommending relevant websites. Specifically, we demonstrated VISTA effectiveness in teaching computer science with an appropriate context. The results of offline feedback evaluation indicate that 86.31% of the teachers found that the information recommended by VISTA was very relevant to both the notes of the teacher as well the real-world images captured. It was observed that the teachers found the real-world connections interesting and they felt it would raise the interest of students in class as well.

The results of qualitative analysis are encouraging enough to work upon the idea on a larger scale. VISTA can be utilized as a suggestive tool outside the classroom also. Some teachers opined that real-world connection, probably the most impactful form of contextual teaching, is also time-consuming due to the length of text in the recommendations. This can be addressed by generating a summary of the recommended websites. Although VISTA is currently attuned to computer science courses, it can be adapted to many disciplines with some modifications. We are working toward making it a generic tool that can be used in any subject. As some teachers stressed upon linking the concepts with recent developments, we shall also prioritize contextualization recommendations that are recently added.

CONFLICT OF INTERESTS

The study was conducted in a technical university where there is no institutional ethics committee overseeing the study with human subjects. However, we have ensured that no subject is disadvantaged under any circumstance. We identified each teacher by a unique ad hoc identifier while conducting the experiment. Gathering of responses and analysis were done through these identifiers rather than actual identities. The data set used in the experiment is anonymous. The authors do not have any conflict of interest to declare.

PEER REVIEW

The peer review history for this article is available at https://publons.com/publon/10.1002/cae.22407

DATA AVAILABILITY STATEMENT

The code for VISTA, the data sets used, and the evaluation details can be accessed at https://github.com/VISTA-NSIT. The Github repository contains the code, graphs, and the contextualized results generated through VISTA that can be accessed by anyone.

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How to cite this article: K. Kanika, S. Chakraverty, P. Chakraborty, M. Madan, G. Gupta, and A. Agarwal, *VISTA: A teaching aid to enhance contextual teaching*. Comput Appl Eng Educ. 2021; 29:1526–1541. https://doi.org/10.1002/cae.22407

APPENDIX

EXAMPLE ILLUSTRATING THE WORKING OF VISTA

INPUTS:

Input: As described in the paper, VISTA takes class notes and an image as input; a snippet of a portion of class notes on artificial intelligence is given below. To relate with these notes, the adjacent image was given as input.

Preprocessing teacher's notes

The OCR extracts the following text from the image of notes:

Artificial	the	machihes	like	The	to	associated	as	ideal
intelligenc	simlation	that	humans	term	any	with	learning	character- istic
A	of	are	and	ma	machihe	a	and	of
I	human	programmed	minic	also	that	human	problem	artificial
refers	intelligence	to	their	be	exhibits	mind	solving	intellighce
to	in	think	actions	applied	traits	such	The	is
Its	ability	to	rationalize	and	take	action	that	have
The	best	chancc	of	achieving	a	specific	goal	a

VISTA corrects all the spelling errors present in the extracted text and gives the following corrected words:

Artificial	the	machines	like	The	to	associated	as	ideal
intelligence	simulation	that	humans	term	any	with	learning	character- istic
A	of	are	and	ma	machine	a	and	of
I	human	programmed	mimic	also	that	human	problem	artificial
refers	intelligence	to	their	be	exhibits	mind	solving	intelligence
to	in	think	actions	applied	traits	such	The	is
Its	ability	to	rationalize	and	take	action	that	have
The	best	chance	of	achieving	a	specific	goal	a

Every word in the list is identified as one part of speech:

[('Artificial', 'JJ'), ('intelligence', 'NN'), ('(', '('), ('AI', 'NNP'), (')', ')'), ('refers', 'NNS'), ('to', 'TO'), ('the', 'DT'), ('simulation', 'NN'), ('of', 'IN'), ('human', 'JJ'), ('intelligence', 'NN'), ('in', 'IN'), ('machines', 'NNS'), ('that', 'WDT'), ('are', 'VBP'), ('programmed', 'VBN'), ('to', 'TO'), ('think', 'VB'), ('like', 'IN'), ('humans', 'NNS'), ('and', 'CC'), ('mimic', 'VB'), ('their', 'PRP$'), ('actions', 'NNS'), ('.', '.')]

[('The', 'DT'), ('term', 'NN'), ('may', 'MD'), ('also', 'RB'), ('be', 'VB'), ('applied', 'VBN'), ('to', 'TO'), ('any', 'DT'), ('machine', 'NN'), ('that', 'IN'), ('exhibits', 'VBZ'), ('traits', 'NNS'), ('associated', 'VBN'), ('with', 'IN'), ('a', 'DT'), ('human', 'JJ'), ('mind', 'NN'), ('such', 'JJ'), ('as', 'IN'), ('learning', 'NN'), ('and', 'CC'), ('problem-solving', 'NN'), ('.', '.')]

[('The', 'DT'), ('ideal', 'JJ'), ('characteristic', 'NN'), ('of', 'IN'), ('artificial', 'JJ'), ('intelligence', 'NN'), ('is', 'VBZ'), ('its', 'PRP$'), ('ability', 'NN'), ('to', 'TO'), ('rationalize', 'VB'), ('and', 'CC'), ('take', 'VB'), ('actions', 'NNS'), ('that', 'WDT'), ('have', 'VBP'), ('the', 'DT'), ('best', 'JJS'), ('chance', 'NN'), ('of', 'IN'), ('achieving', 'VBG'), ('a', 'DT'), ('specific', 'JJ'), ('goal', 'NN'), ('.', '.')]

Selecting core teaching concepts

The system gets informative words by selecting nouns and adjectives. From the text, we get the following informative words:

('artificial', 'JJ')
('intelligence', 'NN')
('simulation', 'NN')
('human', 'JJ')
('intelligence', 'NN')
('human', 'JJ'),
('mind', 'NN')
('learning', 'NN')
('problem', NN')
('solving', 'NN')
('ideal', 'JJ'),
('characteristic', 'NN')
('ability', 'NN')
('best', 'JJ'),
('chance', 'NN')
('specific', 'JJ'),
('goal', 'NN')

All the words and phrases containing the words listed above are picked up as candidate teaching concepts. As this gives us a huge list of words, the candidate teaching concepts are filtered to get core teaching concepts through clustering based on page numbers. Following are the core teaching concepts extracted from the notes:

Society for Artificial Intelligence and Simulation of Behavior (AISB), 985, 986

artificial intelligence (AI), 985, 986, 999

artificial intelligence, 982

AI4People, 1002

AI for Humanitarian Action, 986

AI for Social Good, 986

AI Habitat (simulated environment), 981

Simulation, 981, 982

AI Index, 27

Machine learning techniques, 42, 161, 999

augmented finite-state machine (AFSM),979

Boltzmann machine, 988

brain–machine interface, 11, 971

Center for Human-Compatible AI, 998

Center for Humane Technology, 1007

Acquiring the central theme of image

By searching on the google image search with the image submitted by the teacher as a query, we reach the central theme of the image, **Game controller**.

Creating a cloud of related terms

Base-level categories: Game controller–American inventions, Videogame controllers.

Categories present on the wiki pages of base-level categories.

Videogame controller: Computing input devices, Videogame accessories, Videogame control methods.

American inventions: Science and technology in the United States; North American inventions.

Correlating graph nodes and core teaching concepts

Every core teaching concept is searched for in the graph and a path is extracted between core teaching concepts and image theme. For example, in this case, “game controller” and “artificial intelligence” are connected through the following nodes:

[“game controller,” “input device,” “BIOS,” “firmware,” “software,” “computer program,” “expert system,” “artificial intelligence”]

Similarly, for “game controller” and “human intelligence,” the following is the path:

[“human intelligence,” “intelligence,” “cognition,” “learning or memory,” “memory,” “knowledge,” “sign,” “tab key,” “human interface device,” “input–output device,” “input device,” “game controller”]

Similarly, a list of the terms that are related is prepared for initial web search.

Initial mining of web resources

Search queries are formed using the terms that are somehow related to the image theme. In this particular example,

<“Game Controller” + “Artificial intelligence” + “ Artificial intelligence”> and

<“Game Controller” + “ human intelligence” + “ Artificial intelligence”>

Filtering of most relevant results

The list of stop words is available on GitHub repository of VISTA. Following is the list of websites along with the similarity scores:

URL	Similarity score
https://towardsdatascience.com/create-your-own-board-game-with-powerful-ai-from-scratch-part-1-5dcb028002b8	0.53501
https://www.sheffield.ac.uk/news/nr/how-to-tackle-deal-online-abuse-social-media-gaming-video-games-new-research-tech-1.882350	0.53022
https://www.researchgate.net/publication/333695951_Assistive_game_controller_for_artificial_intelligence-enhanced_telerehabilitation_post-stroke	0.53013
https://medium.com/@shield_ai/a-conversation-with-alex-rozgo-dynamical-systems-engineer-ac76e7c39592	0.41042
https://www.researchgate.net/publication/267636559_Competing_and_Collaborating_Brains_Multi-Brain_Computer_Interfacing	0.37191
https://www.unite.ai/ai-model-might-let-game-developers-generate-lifelike-animations/	0.37004
https://spiral.imperial.ac.uk/bitstream/10044/1/80381/1/Admiraal-M-2020-PhD-Thesis.pdf	0.34340
https://read.hyperight.com/where-are-we-with-ai-and-ml-so-far-a-silicon-valley-perspective/	0.32949
https://www.computer.org/csdl/journal/ci/2017/01/07307180/13rRUwInvno	0.31048
https://link.springer.com/chapter/10.1007/978-3-030-25540-4_36	0.24593
https://blogs.microsoft.com/on-the-issues/2013/02/18/how-computing-research-and-education-drives-positive-impact/	0.24980
https://link.springer.com/chapter/10.1007/978-3-319-03680-9_29	0.21832
https://www.gamedev.net/tutorials/programming/artificial-intelligence/the-total-beginners-guide-to-game-ai-r4942/	0.21803
https://ag.stinguide.site/4520.html	0.20989
https://www.unite.ai/deepminds-new-ai-is-able-to-learn-the-rules-of-a-game-as-it-plays/	0.20640
https://www.hindawi.com/journals/ijcgt/2015/839721/	0.20344
https://builtin.com/artificial-intelligence/ai-games	0.20310
https://www.gamedev.net/tutorials/programming/artificial-intelligence/the-total-beginners-guide-to-game-ai-r4942/	0.20045
https://developer.ibm.com/technologies/artificial-intelligence/articles/machine-learning-and-gaming/	0.20013

Recommended link

Create your own board game with powerful AI from scratch
https://towardsdatascience.com/create-your-own-board-game-with-powerful-ai-from-scratch