KELDEC: A Recommendation System for Extending Classroom Learning with Visual Environmental Cues

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ABSTRACT
We develop an innovative personalized recommendation system called KELDEC that links the notes that students take in class with their outdoor experiences captured with camera, to suggest websites that extend their knowledge. Despite the plethora of educational recommendation systems, there is a dearth of effective tools that make evident the practical application of theory in the real world. KELDEC extracts the core learning points from class notes and distinctive labels that describe objects in a picture. It then mines the web to first extract the technical context of the picture, and subsequently culls out websites that establish linkages between notes and the picture. Response to user surveys garnered from students studying Software Engineering in the undergraduate Computer Engineering course reveal that they gain new and practical extension of classroom knowledge.

CCS Concepts
• **Information systems → Information retrieval → Retrieval tasks and goals → Recommender systems**

Keywords
Personalized mobile learning; Educational recommender system; Classroom learning points; Image analysis; Web content mining

1. INTRODUCTION
Today, the combined use of advanced computing technologies, abundant multimedia data, and streaming communication have steered society towards new paradigms of education such as blended learning and flipped classroom, which conquer the constraints of time and location [1,2]. Indeed, learning is no longer a collective experience of disparate events but a continuous process that progresses even after a student leaves the classroom [3].

There are several educational recommender systems that enable students to find relevant information and educational resources[4]. However, there is a dearth of tools to help dig out serendipitous information by connecting classroom learning to the outside world that the student would not have otherwise discovered. We propose a learning recommender system that makes use of visual stimuli in the dynamic environment that students immerse in after class hours, with the aim of finding extensional knowledge and practical applications of what they have learnt in the class. The system is named Knowledge Extension by Linking Dynamic Environment with Class-notes (KELDEC).

The remaining paper is structured as follows. Section 2 explores existing educational recommender systems with that use images and class notes as learning aids to offer personalized suggestions. Section 3 expounds the working of our proposed learning recommendation system, KELDEC. Section 4 presents the results and analysis of our survey. We conclude and give future possibilities in section 5.

2. PRIOR WORK
It is widely recognized that educational recommender systems assist students by helping them deal with the problem of information overload [5]. A number of educational recommender systems provide various online resources such as learning objects [6], lecture notes [7], and even entire courses [8]. Personalized educational recommender systems use tags with ratings [9], prior knowledge [10], similarity between tags [11] and past experience of students [12] to give learner-specific suggestions. However, it has been observed that with time, the suggestions become obvious, leading to the problem of overspecialization and reduced user satisfaction [13].

The serendipity factor was introduced to improve user satisfaction [11, 13, 14]. In [13], the authors suggest that serendipity should include contextual analysis for suggesting relevant yet unexpected items. Some context-aware recommendation systems do consider time and location information [15]. However, there are other situations where learners leave an imprint of their learning such as

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lecture notes taken in a classroom, which provide a contextual background of their learning. Indeed, several studies discuss the importance of class notes [16,17], but the idea of utilizing such notes as repositories of contextual and personalized learning has not yet been explored. Apart from class notes, images are also reservoirs of latent information. Pictures taken by learners reflect what captures their attention and interests them. Such information can then be utilized to establish linkages between the image and user generated content. The main contributions of this work are:

1. KELDEClinksclass notes with latent information in a picture clicked by a student in real environment. The notes and pics are treated as capsules of personalized and contextual information. They are harnessed to mine information from the web and suggest relevant websites to extend learning.

2. We propose a novel way to identify the central theme discussed in class with the help of class notes and ebook of the subject.

3. We propose a method to extract the technical content that is hidden in an image by creating a dictionary and tapping the web as a knowledge source.

3. WORKING OF KELDEC

The block diagram in Fig. 1 shows the components and overall workflow of the KELDEC system. We now explain its working.

3.1 Pre-process Notes

A student uploads a scanned copy of handwritten class-notes and inputsthelink to a reference e-book. For the sake of illustration, we assume that the student is enrolled in a technical course and looking forward to its application in the real world. With the help of an Optical Character Recognition (OCR) module, the system converts the handwritten notes into a set *K* of words. A spell-checker checks and corrects spelling mistakes in *K* [18].

3.2 Extract Core Learning Points

Noun phrases encapsulate bulk of the information that notes carry [19]. KELDEC first extracts the concepts by selecting nouns from *K*. Given a reference e-book, KELDEC then searches through its index to extract all single-word or multi-word phrases that contain the identified concepts in *K*. All such index topics represent potential learning points that were discussed in class.

In order to identify the core learning points and central theme that was taken up in class, the system first creates clusters of all page numbers corresponding to every index entry in *K*. A dense cluster comprising many close by pages indicates a core theme that was discussed in the class whereas a sparse cluster indicates anecdotal mention. KELDEC picks up the densest cluster and extracts itsindex phrases to form a set *L* of *Core Learning Points* (CLP). Images 1.1 to 1.5 included in the input dataset that we have made available [20], are sample class-notes. List 1 that follows these images contains the list of CLPs extracted.

3.3 Extract Distinct Image Labels

After stepping out of classroom and entering the dynamic environment, a student captures and uploads a picture of a scene or an object of interest. The system performs image analysis to recognize the objects in the image and extract a set of descriptive phrases called *labels* for these objects. Image 2 in the input dataset [20] shows a picture clicked. Its descriptive labels extracted are listed under list 2.

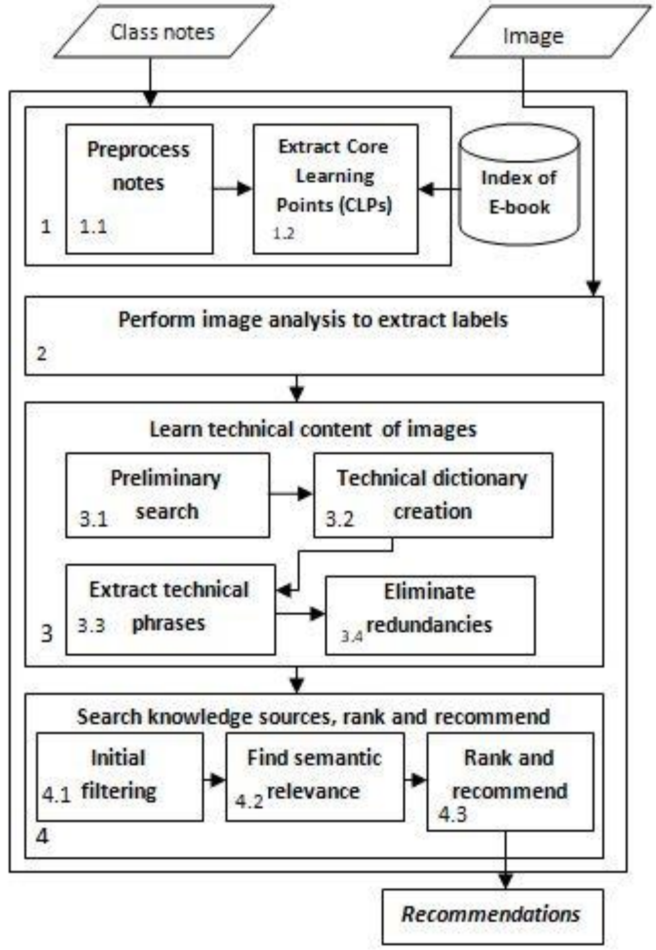

Fig 1: Block Diagram of the KELDEC system

Some of these labels may be repetitive. To eliminate redundant labels and filter out distinct ones, KELDEC creates clusters of all image labels. Each label is treated as a document which can be represented by a vector of Term Frequency-Inverse Document Frequency (TF-IDF) values of the terms collected from all such documents [21]. The pairwise Euclidean distances between these TF-IDF vectors are used to generate the clusters. The label associated with the TF-IDF vector closest to the centroid of each cluster is added to a set *M* of distinct image labels.

3.4 Learn Technical Content of Images

KELDEC now conducts an exhaustive web search to gather technical information related to the set *M* of distinct labels.

3.4.1 Create technical dictionary

The system creates a reference dictionary of common technical words to cull out technically oriented websites related to the image. Starting with a few technical terms, for example, machine, system, device and equipment, their hyponyms and synonyms are extracted from wordnet [22] and added to construct a reference dictionary *D*. List 3 available in the input dataset [25-20] illustrates a portion of this dictionary.

3.4.2 Conduct preliminary search

For each image label *m* in *M*, the system generates three search queries (i) '*m* equipment' (ii) '*m* machinery list', and (iii) '*m* electronic devices'. It then launches a web search on Google search engine for each search query and selects the first ranked website, thus producing a set W_m of three urls for a given label m.

3.4.3 Extract technical phrases

From each website in W_m, the system extracts a set of concept phrases by identifying the regular expression <JJ>*<NN>, where <*JJ*> is an adjective and <*NN*> is a noun. Such combinations, such as *synchronous motor* and *hydraulic machinery* represent descriptive concepts. The system scans through all such descriptive concept phrases collected from all websites in $W_m$and identifies those phrases that contain words belonging to the technical dictionary *D*. It sorts the concept phrases according to the number of overlapping terms with *D,* and selects the top 10 amongst them to generate a set T_m of technical terms related to label *m*.

3.4.4 Eliminate redundant technical terms

In order to remove redundant technical terms from T_m that are highly similar, the system uses a sequence matching algorithm which returns a measure of two sequences' similarity in the range [0, 1], by using Eq. 1

$$r = \frac{2.0 \times l}{n} \tag{1}$$

where, *n* is the combined length of both the sequences and *l* is the length of their longest contiguous matching subsequence. If the similarity score *r* is greater than 0.7, then the technical phrase with the shorter length is rejected in favor of the longer one. Image 2 in input dataset [20] is a sample picture and its technical phrases are enlisted in list 4.

3.5 Mine Knowledge Sources

KELDEC now uses cues from both T_m,the set of image-related technical phrases and *L*, the class notes' CLPs, to scout for relevant websites. The system issues a search query for every combination of technical phrase *t* from T_m and CLP phrase *p* from *L*, also appending the name s of the subject being taught, to form a search query <*t,p,s*>. It chooses the top ranked web page for each search query to generate an initial recommendation dataset R_{mL} of URLs. It may be noted that each website in R_{mL} originates from a distinct image label m via one of its relevant technical terms and from L via one of its a CLPs.

3.5.1 Filter out unrelated urls

KELDEC applies the following filters to remove irrelevant websites from R_{mL}:At least one of the CLPs in *L* must be present in the website, else it is eliminated from R_{mL}. Wiki articles and community forums are removed as they tend to be too generic and broad-based. URLs whose documents that contain a preset list of stop_words such as 'amazon', 'wikipedia', and 'youtube' are thus eliminated.

3.5.2 Calculate semantic relevance

KELDEC now assesses the semantic closeness of each article in R_{mL} with both the image label m as well as to the CLP *p* that helped mine it from the web. We employ pre-trained word embeddings based on the GloVe (Global Vectors for Word Representation) algorithm by Stanford [23]. They represent words with vectors that encapsulate semantic information of the words. For each article in R_{mL}, special characters are replaced with blank spaces as they do not add meaning to the article. The system removes all stop words as defined by the NLTK stop-word corpus. The article's textual content is then tokenized into a set of word-frequency pairs $A=\{(w_1,f_1), \ldots (w_i,f_i), \ldots (w_n,f_n)\}$, where $w_i$occurs with a frequency f_i .

Let us consider a multi-word phrase $X = \{l_1,l_2, l_3, \ldots , l_n\}$ which may be either an image label *m* or a CLP phrase in *L*. The semantic similarity between article *A* and *X* is given as:

$$Similarity(A, X) = \frac{\sum_{(w_i, f_i) \in A} \sum_{l_j \in X} f_i \times Similarity_{ij}}{|A||X|} \tag{2}$$

$$Similarity_{ij} = \frac{\vec{w}_i \cdot \vec{l}_j}{|\vec{w}_i||\vec{l}_j|} \tag{3}$$

Where $\vec{w}_i$ and $\vec{l}_j$ are the vector embedding representation of w_i and l_j respectively and $|A|$, $|X|$ are the respective lengths of the article *A* and phrase *X* [24].The overall semantic similarity score for a given image label phrase *m* in *M* and a CLP phrase *p* in *L* is a linear combination of a prefixed weighting factor *α*:

$$Similarity_{score} = \alpha \times Similarity(A, p) + (1 - \alpha) \times Similarity(A, m) \tag{4}$$

The weighting factor *α* determines whether the recommended site is semantically closer to the image or to the class notes.

3.6 Rank and recommend

The filtered set of websites obtained from each of the image labels in *M* and each CLP in *L*, together form the final recommendation set *R*. The websites are sorted according to their similarity scores given by Eq. 4. Finally, KELDEC recommends the top-N of these websites to the user.

4. EXPERIMENTAL RESULTS

KELDEC is developed as an Android application that interacts with a Node.js server. On receiving inputs, the server spawns python scripts, for each step, and formulates the required search queries. We used Google Cloud Vision OCR to extract text from the pdf of notes [25]. It detects and extracts text using convolutional neural networks. Cloud Vision is also used to extract image labels. The software uses the existing metadata of images maintained by Google to detect objects present in an image. After detecting objects and labels, the system performs landmark recognition with the help of knowledge graph entities to locate landmarks and improve the accuracy of identification [25]. We used the Google search engine to mine technical terms related to image labels and the relevant websites for recommendation. The Selenium WebDriver was used to gather information from the Web. The value of the weighting factor α was preset to 0.5.

Datasets: UG students of B.Tech Computer Engineering in NetajiSubhas University of Technology (N.S.U.T.), study the course Software Engineering during their fourth semester. We took class notes taken by students during three lecture periods on the themes (*L1*) software development lifecycle models, (*L2*) requirements engineering and (*L3*) a revision of data flow diagrams and capability maturity model. Each student also submitted a picture of an object or scene of interest, that they had clicked in their immersive environment after stepping out of class.

For evaluation purpose, we used three randomly chosen pairs of notes and images. The first image, paired with *L1*, was that of a laptop, a portable speaker and a wire. The second image, paired with *L2*, was that of a few people performing on stage with some musical instruments. The third image, paired with *L3*, was that of a bicycle and a small lamp in the corner. We have made available all the datasets and links to the recommended articles generated for each dataset in github [26].

Survey Questionnaire: We conducted a survey-based offline evaluation of the KELDEC system to assess the recommendations generated for their degree of relevance to students' knowledge and the extent to which they offered an element of serendipity. The survey questionnaire comprised two psychometric questions and one qualitative question, as given below:

Que. 1: *To what extent do you find the information on this website relevant.*

Respondents are required to rate the relevance on a 5-point likert scale [27]. The classes denote 1: very relevant 2: quite relevant 3: somewhat relevant 4: hardly relevant 5: irrelevant.

Que. 2: *To what extent did the information present on the website surprised you.*

Respondents are required to choose one class, on a 3-point likert scale; 1. Very surprising, 2.somewhat surprising 3.not at all surprising.

Que. 3: *Write your experiences on using this app.*

Whereas the first two questions are based on the recommendations given by KELDEC for the sample datasets, this question sought users' own experiences with the recommendations generated specifically for their own datasets.

Survey Response: A total of 74 students enrolled in the software engineering course of BTech, Computer Engineering at N.S.U.T., participated in the survey by engaging with the KELDEC system in two ways.

1. Each participated first interacted with the app to input their own class notes and pictures and receive recommendations for further reading.

2. For each sample datasets, the corresponding class notes and image pairs were input to KELDEC. The system recommended the Top-2 websites for each dataset. Respondents were requested to study each sample dataset and then browse the top two recommended websites carefully.

The participants finally responded to the three questions in the survey. Table 1 summarizes the responses for relevancy of the recommendation and Table 2 summarizes the responses for their serendipity. The Top-2 recommendations generated are labeled as url-1 and url-2 under column 2.

(i) Relevancy: Table 1 shows that the response for relevancy varied for different urls. Dataset II url-1 and the Dataset III url-2 gained the best scores for relevancy with both median and mode at class 2. Thus the most frequent and concentrated response was quite relevant. Dataset II url-2 generated the most frequent response at class 2 - quite relevant, with a slight tilt towards class 3 - somewhat relevant. Dataset I url-1 was judged predominantly as somewhat relevant with both median and mode at class 3. Dataset I url 2 and Dataset III url 1 had the most frequent response at somewhat relevant but also reflected a wide variation with the median value at 5 - irrelevant. Overall, 9.8% of respondents found the recommendations to be very relevant, the largest group comprising 21.5% of respondents voted for them to be quite relevant, 17% found them to be somewhat relevant, 12.7% of them found them hardly relevant and 12.3 % found them to be irrelevant.

Table 1. Results for relevance

Dataset	Top-2 ReccUrls	Relevancy classes					Median Class	Mode Class
		1	2	3	4	5		
I	url-1	7	10	21	20	15	3	3
	url-2	7	13	18	16	20	3	5
II	url-1	12	37	14	5	5	2	2
	url-2	7	26	18	13	10	3	2
III	url-1	8	15	15	14	21	3	5
	url-2	18	28	16	8	3	2	2
Users' response to the question: To what extent do you find the information on this website relevant								

Table 2. Results for serendipity

Dataset	Top-2 ReccUrls	Serendipity classes			Median Class	Mode Class
		Very Much	Some what	Not at all		
I	url 1	9	45	18	Somewhat	Somewhat
	url-2	16	38	18	Somewhat	Somewhat
II	url-1	23	40	9	Somewhat	Somewhat
	url-2	22	32	19	Somewhat	Somewhat
III	url-1	17	30	26	Somewhat	Somewhat
	url-2	19	38	16	Somewhat	Somewhat
Users' response to the question: To what extent did the information present on the website surprised you.						

(ii) Serendipity: The responses to the question investigating the surprising element in the recommendations clearly indicate that more than half of the participants found the information somewhat surprising for each recommendation. Statistically, 24.37% of respondents considered the recommendations very much surprising, a majority of 51.26% found them somewhat surprising and 24.37% found no element of surprise.

(iii) Qualitative response: Responses to the qualitative question reflected overall enthusiasm towards the potential of the app and added some new practical dimension to the theoretical knowledge gained in class. The most frequent responses was- "I would definitely use the app". Some expressed "Needs improvement". Many respondents felt that the length of the textual matter on recommended websites was an issue - the articles needed to be pruned to show the relevant portion or the gist of the information. Feedback generally indicated that students would like to use the app in future, but preferred certain knowledge sources such as news portals that report the latest news on the topics they learnt in class.

5. CONCLUSION

We developed KELDEC- a recommender system that uses visual cues from the dynamic environment of learners to suggest online resources that offer extensional technical knowledge. To the best of our knowledge, it is for the first time that an automated system brings out the correlation between knowledge acquired in class and the real-life environment of learners. The results of our survey indicate that the recommendations provided are quite relevant. The inclusion of real life images indeed gave information that surprised the students.

Even though we have considered a technical domain, the basic principles of KELDEC can be applied to other fields such as social sciences, literature or fine arts with minor adaptations. Keeping in mind the feedback from participants, we will summarize the recommended sources to reduce length and provide relevant core information. We will also give relative priorities to different categories of knowledge sources as desired by users.

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