AN APPROACH TO SEMANTIC EDUCATIONAL CONTENT MINING USING NLP

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ABSTRACT

The COVID-19 epidemic had caused one of the most significant disruptions to the global education system. Many educational institutions faced sudden pressure to switch from face-to-face to online delivery of courses. The conventional classes are no longer the primary means of delivery; instead, online education and resources have become the prominent approach. With the increasing demand for supplementary course materials to fulfill the needs of each area of study, students began to use search engines and online resources that contain discussions, practical demonstrations, and tutorial videos to aid students in their studies and course work. This study addresses the underlying challenges of retrieving relevant online educational materials by introducing an intelligent agent for semantic data mining. It works as middleware infrastructure that allow context-aware data processing and mining. YouTube was used to assess the consistency of the proposed model since it returns a large number of results in its search pool. The results showed that using the extraction of topics method, the similarities scores with the proposed model provided favorable results. Furthermore, an improvement in video ranking and sorting was realized. According to the findings, using this method provided users with a more productive and reliable study experience.

KEYWORDS

Information Retrieval, E-Learning, Natural Language Processing, Intelligent Agent, Semantic Data Mining

1. INTRODUCTION

On January 30, 2020, the World Health Organization declared the COVID-19 outbreak a global health emergency that caused a massive shift world wide's education system (Oyedotun, 2020). This crisis created an immense disruption of the education system that affected the teaching pedagogy. Educational institutions worldwide have seen a dramatic change in the educational system and faced a sudden pressure to switch from face-to-face to online delivery of courses (Kedraka & Kaltsidis, 2020). Due to the closure of educational institutions caused by COVID-19, conventional classes are no longer the primary means of delivery. Instead, online education has become the prominent approach where learning becomes virtual, practical, and smart (Raja & Nagasubramani, 2018). Closures of educational institutions will continue to substantially affect education, opening a path to exploring innovative teaching strategies to ensure learning continuity during pandemics. Alternately, the closures of educational institutions hinder the provision of essential services to students, specifically in accessing learning facilities such as the library and laboratory rooms where learning resources can be found to aid students in their studies. This poses a challenge in the current educational system to provide students with relevant online resources to support online learning besides course slides, handouts, and manuals to fulfill the needs of each area of study.

Students have unlimited learning resources which can easily be accessed online to help them in their assignments, projects, and learning (Yılmaz & Orhan, 2010). According to Li and Lalani, students can retain an average of 25% to 60% of materials when learning online (Li & Lalani, 2020). Similarly, existing research on the use of online learning resources reveals that it improves students' achievements and positively impacts students' academic self-confidence because they provide them with extra information that is required (Alshahrani et al., 2017). Although abundant materials are accessible online, there is a challenge finding suitable materials online. Retrieving relevant online materials is critical for online education as students rely heavily on it in researching their homework and assignments, which are the standard assessment methods in online education. Searching online for relevant materials can be a burden as different resources are within the search pool. Students may consume much time browsing all search results and, later on, find that these results are irrelevant (Biaz et al., 2014).

This research seeks to address these issues by introducing a data-driven approach to improve the retrieval of relevant educational materials online. The proposed approach extracts topics from the course syllabus and uses it to retrieve the most relevant and valuable materials online, reduces the time consumed in searching, and improves the search results to aid students in studying and course work. Additionally, the approach is based on two factors to determine the relevance of online materials. The first factor depends on retrieving information or the materials from websites and other online educational resources. The second factor is the ranking strategy to determine the most relevant resources online among the search pool. These factors will help us achieve our objectives to provide relevant educational materials to aid students in their studies and course work and lessen the time spent searching educational materials online.

The remainder of the paper is organized as follows: Section II presents the overview of previous studies related to online learning and discusses the different ways to cope with the COVID-19 pandemic in education. Section III presents a detailed discussion of the proposed model. Section IV describes the methodology to be used in this study. Section V provides the results, and the discussion will be in Section VI. In Section VII, the conclusion of the study is presented.

2. LITERATURE REVIEW

Several studies have shown the importance of online learning during the COVID-19 pandemic. One of these studies is "Freedom of learning in the 'elementary arts and culture' subject the character-based COVID-19 pandemic". The purpose of this study is to find the ability of students in the academic field to study online during the Covid-19 pandemic from February 2020 and to find out the advantages of online. The study results show that Covid-19 has a significant impact on education at the University of Muhammadyah Malang. Home teaching and learning processes utilize Edmodo, Google classroom, etc. The study also presented that employing educational YouTube videos can improve teaching, communication, and motivation for students to learn (Restian, 2020).

The school's readiness and response to COVID-19 in terms of pedagogy, curriculum, and assessment were investigated in a recent study (Gonzales, 2020). The researchers gathered data from the school's teachers to have a clear understanding of the main issues and listen to some proposed solutions. Finally, the researchers proposed a model focusing on six factors that are believed to be the most critical factors, which are, ICT Literacy Training, Stakeholder's Educational Equity, and Re-engineering of Teacher's Mindset, Pedagogical Innovation, Re-designing of the Curriculum, and Re-evaluation of Assessments and Grading System. Moreover, researchers in Georgia aimed to study the country's capacity to continue the education process in the online form of distance learning. This is done by making a case study where online learning using the Google Meet platform was implemented in a private school. The statistics of this case study showed that the quick transition to online education went successful. The experience of this study can be helpful for other countries that have not found the proper ways of change (Basilaia & Kvavadze, 2020).

Another study has been conducted to analyze the reliability and quality of YouTube educational content in the healthcare field. The overall result of the study shows that educationally useful videos are higher than non-educationally helpful videos with a 55.7% score (Lim et al., 2018). Although YouTube is known as an entertainment medium, it has become one of the popular learning platforms. Kohler and Dietrich (2020) recognize that YouTube has evolved into a complementary learning platform that promotes on-demand learning with instructional films and that educational videos are viewed as a successful method for improving a user's knowledge. However, the authors feel that it is important to distinguish educational films used in classrooms from educational videos found on YouTube. Also, a study was made to evaluate the quality of some areas related to medical information about COVID-19 on YouTube as educational resources for dental practitioners. YouTube was used to search for the phrases COVID-19 and dental practice, which yielded 1102 videos. Ultimately, the study results show that YouTube can provide relevant educational information (Yüce et al., 2020).

On the other hand, an evaluation has been conducted over the usefulness of YouTube videos as a health education tool for diabetes self-management. According to the article, the result of the evaluation shows that the probability of getting false information is high compared to finding useful information (Gimenez-Perez, 2018). Despite the availability of these professional education channels, YouTube is nevertheless filled with unpleasant and deceptive information that casual learners are forced to filter through when doing searches (Maynard, 2021). Anyone can use YouTube to post their own User Generated Content (UGC) by creating a personal YouTube channel and then uploading videos in his channel. Additionally, other users can subscribe to channels that they are interested in so they can follow the newly uploaded videos. Although YouTube is famous as an entertainment medium that is a non-educational platform, it became a valuable learning resource for many users and is considered an alternative to written text (Chintalapati & Daruri, 2017).

Information Retrieval offers more advanced tools in learning community and the mobile devices expands the educational activities thru collaboration and sharing of information (Parmigiani et al., 2016 & Meisalo et al., 2004). A video retrieval system in early 2000s (Milrad et al., 2004) was designed and implemented to enable semantic search for specific portions of a video clip in a library of educational digital movies. Gil et al., (2011), developed models and strategies for information retrieval that addressed by distributed information retrieval, often known as federated search. Finding the relevant materials in rich content resources could be a difficult task and time-consuming because of the enormous amount of search results that are generated. For example, the YouTube search ranking system looks through hundreds of pieces of content (Southern, 2020). Hence, it is essential to identify the right search keys when retrieving materials. Natural language processing (NLP) techniques were used by (Guitart et al., 2016) to extract information from the syllabus and to assess course materials. In information retrieval, it is important to evaluate the relevance of each result. The most prevalent measures for evaluating retrieval performance are recall and precision ratios. It was used by Guo & Zhang (2013) to assess the effectiveness of their semantic retrieval technique.

In this study, a semantic-based middleware model was proposed that applies NLP to extract topics from the course syllabus/outline and utilize them as a search key. Since a given rich content online resources will yield a large number of results in its search pool, another layer was proposed using a semantic text similarity analysis and ranked these results to get the most relevant materials based on the extracted topic.

3. PROPOSED MODEL

The proposed approach presents the architectural design of the semantic-based middleware model. It is divided into two main stages: topics extraction and topics enhancement. Figure 1 shows the proposed process model.

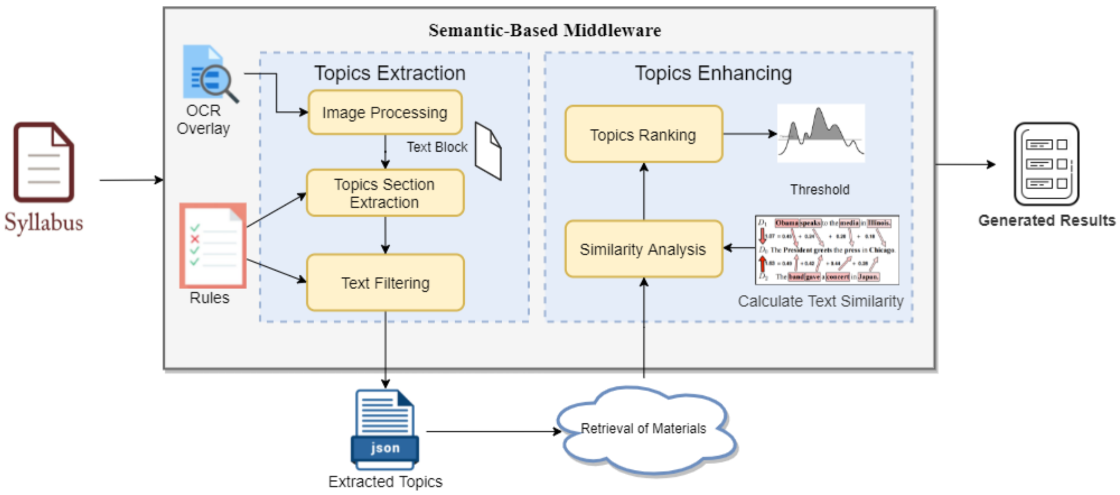

Figure 1. Semantic-Based Middleware Model

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3.1 Topics Extraction

Extraction and recognition of text are principal stages in building efficient indexing and retrieving data (Misra et al., 2012). The approach utilizes topics either by uploading as text or captured from the syllabus. In this study, it is assumed that topics in the syllabus are properly sorted out. Extraction of topics will employ Optical Character Recognition (OCR) to highlight and extract the content of the syllabus. The processed syllabus image returned only as a text block in JSON format. The extracted text will be used to filter all course topics from a course syllabus at one time. In order to have a cleaner result, common keywords, e.g., “topics,” “weeks,” “lecture,” “assessment,” “project,” “assignment” from the syllabus, are excluded from the extraction as shown in Figure 2.


```
["Introduction to Object Oriented
Programming", "Introduction to
Java","OOP main concepts: Objects
vs Classes Identifying", "Objects",
"UML class diagrams", "Modularity
& Encapsulation", "Inheritance &
Polymorphism"]
```


Figure 2. Sample extracted topics

3.2 Topics Enhancing

Once materials are retrieved, each extracted topic from the text extraction process will be queued for semantic text analysis. This study uses the term-based text similarity measures. Cosine similarity as shown in Eq. (1), a known technique of NLP, to find the closeness of two texts which operate on string sequences and character composition (Gomaa & Fahmy, 2013). The approach investigates the distance between two texts (A, B) for comparison and matches our requirement in comparing the title of retrieved materials and the topic titles. Then, the score results of all processed text similarities are stored and used for the ranking process.

$$similarity = \cos(\Theta) = \frac{A.B}{|A||B|} = \frac{\sum_{x=1}^{n} A_i B_i}{\sqrt{\sum_{x=1}^{n} A_i^2}\sqrt{\sum_{x=1}^{n} B_i^2}} \quad (1)$$

After calculating text similarities, a novel ranking strategy will be applied to the retrieved materials to sort and rank the results. Behnert & Lewandowski (2015) discussed that presenting the result in a manner where the most relevant topic comes first before the less relevant topics is a way for us to assist every user in determining the significance of every search result. The proposed approach ranks the materials based on the score from text similarity analysis and sorts them out where the highest similarity scores will be at the top. This stage also includes a threshold, meaning any retrieved material scores less than the threshold value will be skipped, and the ones within the threshold range will be used. Sorted and ranked materials are then displayed on the application with the helped of WebView.

Algorithm 1 shows the topics ranking algorithm.

Algorithm 1

```
Input: Course Syllabus (Si)
Output: Sorted and Ranked Supporting Materials (Vi)
Ti ← Course Syllabus
foreach ti at Ti do
    SupMat-ti ← retrieve materials for each topic
    end for
foreach ti at SupMat-ti do
    tiScore ← calculate Semantic Similarity of the extracted topic and
    SupMat − ti

    if (SupMat − tiScore > th) then
        SupMat-tiScore ← tiScore
    end for
Sort SupMat-ti descendingly
```

4. RESEARCH METHODOLOGY

In order to evaluate this approach, YouTube was used, which is an online platform that includes enormous learning materials. To execute a simulation, five syllabuses were retrieved from online resources coming from different areas and levels of education (higher education, K to 12, and online courseware); Introduction to Algorithms (MIT OpenCourseWare), Data Science (University of Cambridge), Object-Oriented Programming 1 (King Faisal University), Grade 7 Science (K to 12 Curriculum from the Philippines), and Grade 6 Math (International Schools Group – Dammam) are used on this experiment. To process and extract topics from the syllabuses, Space OCR (Free OCR API, n.d.) and Optical Character Recognition API (Application Programming Interface) were used, which allows a simple way of parsing images and getting the extracted text results returned in a JSON format.

Extracted course descriptions and a list of topics are then fed to the search API. YouTube provides a data API that enables other platforms to retrieve YouTube videos to their applications. Based on the user interaction, YouTube will suggest videos. YouTube Data API (API reference, n.d.) was used, and the result is a simulated search on behalf of the user that supplies a limited result (Malik & Tian, 2017). The materials used in the ranking process started after retrieving all the videos and their data. Retrieved materials are stored and queued for text similarity analysis. The application uses TwinWord's Text Similarity API (Natural language processing APIs, n.d.) to compare each result to the topic title. The end result is sorted in a descending manner, in which materials with the highest similarity result will be on the top of the list.

5. RESULTS

The model's performance was assessed after executing the simulation using five syllabuses retrieved from online resources as discussed in the experimental setup, one topic per syllabus was used, which includes "Introduction to Object-Oriented Programming" (experiment 1), "Characteristics of Waves" (experiment 2), "The Number System" (experiment 3), "Binary Search Trees" (experiment 4), and "Linear Modelling" (experiment 5).

In identifying the best criteria for retrieving the relevant materials, two methods were tested. The first method was searching the relevant materials using the extracted course description and calculating the text similarity between the titles of the retrieved materials and the course description. The second method was searching relevant materials using the extracted topics and calculated the text similarity between the titles of the retrieved materials and the extracted topic titles. The Custom Search JSON API was used to dynamically retrieve the materials (Custom Search JSON API, n.d.). For simplification, Table 1, shows one of the experiments that shows the course description and title of the retrieved materials and the corresponding text similarity scores, and Table 2, shows the sample retrieved materials and their corresponding text similarity scores from the extracted topic title. Figure 4 to Figure 8 shows the graphical representation of results for text similarity scores of retrieved materials titles with course description from the syllabus.

Table 1. Sample retrieved materials using course description

Course Description	Title	Similarity Score
The purpose of this course is t	JS: Drawing & Animation | Computer programming | Khan ..."	0.442
provide students with	"Planning a programming project (article) | Khan Academy"	0.226
fundamental knowledge of	"Teaching guide: Intro to JS - Object-oriented design (article)."	0.323
Object-Oriented Programming	"Welcome to SQL (video) | SQL basics | Khan Academy"	0.348
(OOP).	"Random walks (article) | Randomness | Khan Academy"	0.651

Table 2. Sample retrieved materials using extracted topics

Course Description	Title	Similarity Score
Introduction to Object-Oriente	"Introduction of Object-Oriented Programming - GeeksforGeeks"	1.00
Programming.	"Object Oriented Programming in C++ - GeeksforGeeks"	0.744
	"Object Types | Object-Oriented Design | Intro to JS - Khan "	0.857
	"Java Tutorial: Introduction to Object-Oriented Programming"	0.838
	"Intro to Objects - Computer programming - Khan Academy"	0.506

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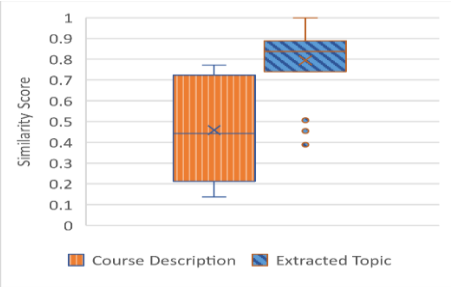

Figure 3. Scores of similarities in experiment 1

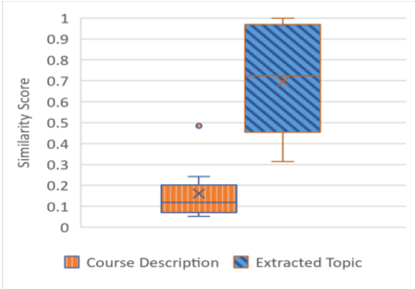

Figure 4. Scores of similarities in experiment 2

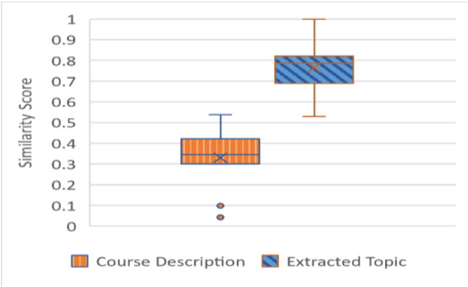

Figure 5. Scores of similarities in experiment 3

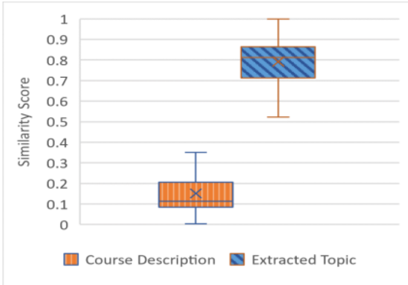

Figure 6. Scores of similarities in experiment 4

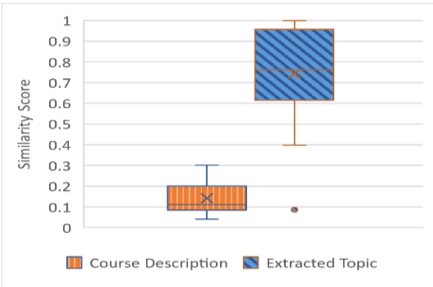

Figure 7. Scores of similarities in experiment 5

From Figure 3 to Figure 7, it is observed that the average scores of the retrieved materials using course description from five experiments ranges between 0.05 (low score average) to 0.49 (high score average), which is relatively low. Searching using the course description gives a large area of results which produces a low score in text similarity analysis between course descriptions and the result titles.

This also shows the results of the proposed approach, which calculates the similarity between the titles of the retrieved materials and the extracted topics. To simplify the discussion, one extracted topic per syllabus was selected from the experiments. It was observed that the result gave a much higher average score and ranged between 0.09 (low score average) to 0.80 (high score average), which is better compared to the similarity score with the course description. This happened as the search result was narrowed to a specific topic from the syllabus hence giving a higher similarity score.

Considering the results, the second method in the model was applied, which uses extracted topics from the syllabus in searching relevant topics on YouTube as it shows a much higher efficiency in similarity tests.

After retrieving the top twenty materials per topic, the similarity score between the retrieved video's titles and the extracted topics used in searching were calculated. Figure 8, shows the five experiments results and with average scores ranging between 0.36 (low score average) to 1 (high score average).

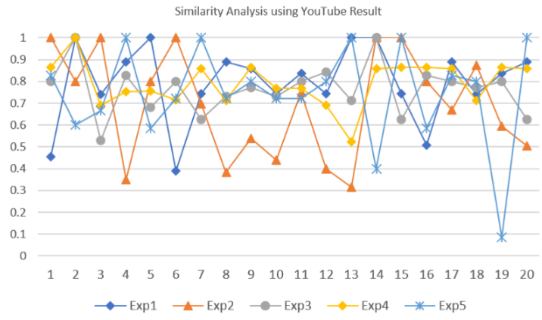

Figure 8. Similarity scores of unranked YouTube results from five experiments

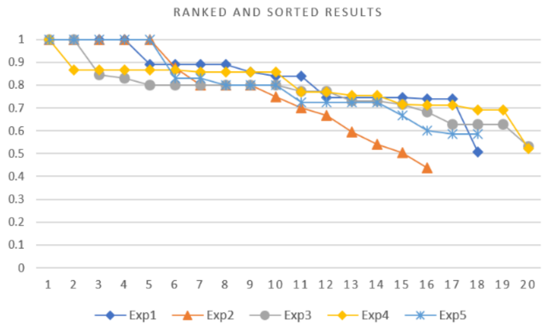

Figure 9. Ranked and Sorted Results

It can be observed that the videos can now be ranked and sorted based on the relevance to the topic according to the text-similarity scores and discard some results that are below the 0.4 thresholds, as shown in Figure 9.

6. DISCUSSION

This study used NLP to introduce a semantic-based middleware approach to address the underlying issues of accessing suitable online educational content. Filtering the list of topics was challenging, especially when the syllabus and course outline were using different layout formats. The best criteria for retrieving materials were also identified, and the two tested methods: searching using the course description and using the extracted title of each topic. Each method used five different syllabi with a total of 100 test samples per method. Table 3, shows the comparisons of the result of this experiment.

Table 3. Comparison between text similarity scores result from five experiments

	Low Score (Ave)	High Score (Ave)
Scores of similarities with the course description	0.05	0.49
Scores of similarities with the extracted topics	0.09	0.80
Scores of similarities with the YouTube Result	0.36	1.00

Searching using the course description method gave a large area of results which produced a low score in text similarity analysis between course descriptions and the titles of the retrieved materials. On the other hand, the result of the proposed approach using extracted topics title on the syllabus produced a higher average score (0.80), which gave an edge in retrieving many relevant materials from external sources and contributed to the high average score (1.00) in similarity scores with YouTube results from the five experiments conducted. One-Sample T-Test (One sample T test, 2021) with a Confidence Interval of 95% was run to assess if the similarity scores from extracted topics differ significantly in comparison with the similarity scores using the course description method. The descriptive statistics showed a mean of 0.4706 from similarity scores of the proposed approach with a 0.2680 standard deviation. Table 4, shows the result ($t(99)=7.936$, $p < .001$) and reveals a significant difference in score similarities of extracted topics.

Table 4. One Sample Test result

	Similarities Scores of Extracted Topics
Mean	0.4706
Std. Deviation	0.2680
t	7.936
df	99
Sig (p)	< .001
Mean Differenc	0.2127

Note: Test Value =0.257862(Mean similarity score of Course Description method)

Even though the five experiments came from different levels of education, it can be observed that the area of concern does not affect the retrieval of data on YouTube. To evaluate the relevance of the retrieved materials, recall and precision were used, as discussed in (Arora et al., 2016). In the conducted experiments, 100 materials were retrieved from YouTube using the extracted topics and filtered 93 relevant materials using a threshold of 0.4 in the text similarities scores. This resulted in a recall of 93% using Eq. (2) and a precision of 100% using Eq. (3).

$$Recall = \frac{Relevant\ Materials}{Total\ Retrieved\ Materials} \quad (2)$$

$$\text{Precision} = \frac{Relevant\ Materials}{Actual\ Relevant\ Materials} \quad (3)$$

The result also shows that retrieved materials from YouTube are not ranked and not sorted for the user. Figure 9 presented the ranked and sorted result using the similarity scores of each material from highest to lowest. This helped in serving many relevant videos to be on the top of the list.

7. CONCLUSION

COVID-19 pandemic changed the way education is delivered. Number of governments moved to the online platform to overcome the virus outbreak and to keep social distancing. The study incorporates the Artificial Intelligence as an attempt to improve the results of information retrieval. It employs natural language processing (NLP) techniques to ensure data relevancy. The proposed approach utilizes an intelligent agent for semantic data mining and works as middleware infrastructure that allow context-aware data processing and mining. With the condition right now, it is crucial for learners to study from relevant educational materials to their courses from reliable online resources. Upon further reflection, the proposed system revealed some limitations that can be avoided in future work. One of the limitations is, the proposed system only supports the English language. Finally, it is identified that the initial results are auspicious. With proper authorizations, YouTube search API allows us to manipulate the feeds, and based on the test and observations conducted, the model improved the information retrieval quality in a rich content online resource. However, this framework was only applied to the YouTube platform. The content quality of the retrieved video materials is not assessed on this study. Future study may include the different factors in assuring the content quality by including the video category which to date is not used by YouTube in its search functions and the number of likes, dislikes, and views. This experiment concludes that using this approach gives the users a better study experience efficiently and effectively.

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